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Smart home on the rise? The role of trust and privacy in technology acceptance of smart home devices

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ABSTRACT

In recent years, smart devices have been more prevalent in people's homes. In this context, this study analyzes the role of trust and privacy in technology acceptance of those devices. Derived from theoretical considerations, we form eleven hypotheses and test them by structural equation modeling (SEM). The analysis relies on data from a quantitative survey on smart thermostats with 324 participants from Germany. The results indicate a strong positive total effect of trust and a negative impact of privacy concerns on the intention to use, showing the special relationships of those factors in the context of smart home technology.

Keywords: Smart home, technology acceptance, trust, privacy.

INTRODUCTION

In the past, only people were smart, today things are too. Over the past few years, the word 'smart' has become an umbrella term for all innovative technologies that are based in some form on artificial intelligence. The main feature of these smart technologies is their ability to capture information from the environment and to react to it independently (Marikyan et al., 2019). Thanks to the multitude of resulting advantages for everyday life, such technologies quickly found their way into the homes of many people. There, they are gradually making the innovative smart home concept a reality (Darby, 2018). There is already a smart alternative to almost every conventional household item. The market for smart home devices is booming and growing steadily. According to Statista (2021), the volume of the German smart home market will grow from around €5,407 million in 2021 to €9,259 million in 2026. This corresponds to an annual sales growth of 11.36%. The German smart home market is becoming more and more lucrative for manufacturers and the potential is far from exhausted. According to a representative survey by Splendid Research (2020), only 40% of Germans use smart home devices at all. In addition, very few of them (18%) actually connect several devices to form a smart home system. At least 38% of Germans are interested in using it, while 22% still categorically reject it. One of the most frequently mentioned concerns in connection with smart home devices, apart from the high acquisition costs (52%), is the concern for privacy (45%). In contrast to users in the USA or Great Britain, German users take a critical view of the subject of data protection in smart homes. They do not want to disclose their personal data and are very concerned about misuse (Infratest dimap, 2020).

The acceptance of smart home devices is a basic requirement for their market success. Lately, the speed at which these technologies get accepted is additionally driven by the COVID-19 pandemic. Since its beginning, the amount of time people are working, studying, and socializing at home has highly increased, especially during lockdown times. This development results in even more home upgrades using smart home devices. However, its rapidity also has implications for thoroughly thinking through any potential risks that come with these devices. The more this technology is accepted, the more insights into private life and the data generated will be given. Hence, a lot of trust in smart home devices is required (Maalsen & Dowling, 2020).

In the field of acceptance research, various impact models for the general prediction of technology acceptance have already been developed and checked. Some of these models are already being used in the context of smart home devices as well. However, trust and privacy concerns have been rarely taken into account yet. This paper aims to meet this research need and to make a decisive contribution to technology acceptance research in the field of smart home devices. Consequently, we come to the following research question:

What role do trust and privacy concerns play in the technology acceptance of smart home devices in Germany in addition to its main drivers?

To answer this research question, we form hypotheses based on an extensive literature research and conduct a quantitative survey study – the resulting data from the survey is analyzed by structural equation modeling (SEM).

The remainder of this paper is structured as follows: After this introduction, we present related work, based upon which we will derive hypotheses resulting in our conceptual model. Subsequently, we introduce our methodology and structure of the empirical study, before we present the statistical results. Finally, we discuss those results and conclude the paper.

RELATED WORK

This section covers related work addressing the acceptance of innovative technologies, including smart home devices.

The theory of reasoned action (TRA; Ajzen & Fishbein, 1970, 1973; Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB; Ajzen, 2005) form the basis for various sub-areas of acceptance research and thus also for that of technology acceptance. According to Schäfer and Keppler (2013), this includes various research strands that deal with such different aspects as the individual user acceptance of larger and smaller technical artifacts (e.g. mobile phones, office technology, software), through to the social acceptance of new and/or risky technologies (e.g. nuclear energy, genetic engineering). Based upon these theories, the seminal technology acceptance model (TAM; Davis 1986; Davis et al. 1989) was developed which specifically deals with the prediction of the acceptance of primarily new technologies and systems (see Figure 1). As opposed to the TRA and the TPB, it only considers the attitudinal component of behavioral intention (Davis, 1986). Based on the perceived innovation characteristics according to Rogers (1983), attitude toward using in the context of the TAM consists of two main behavioral beliefs: perceived usefulness as "the degree to which an individual believes that using a particular system would enhance his or her job performance" (Davis, 1986, p. 26) and perceived ease of use as "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, 1986, p. 26). The predictive power of the TAM has been shown significantly with the help of data from 107 surveys of full-time MBA students in the USA on their voluntary use of a word processing program (Davis et al., 1989). Over the years, the TAM has been enhanced several times. In 2000, the TAM2 was presented (Venkatesh & Davis, 2000) and the TAM3 in 2008 (Venkatesh & Bala, 2008). In both cases, the researchers looked at the factors behind each of the two main behavioral beliefs in more detail. In addition, other functional and hedonic antecedents of behavioral intention were examined and recorded in the context of their unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) and its extension (UTAUT2; Venkatesh et al., 2012).

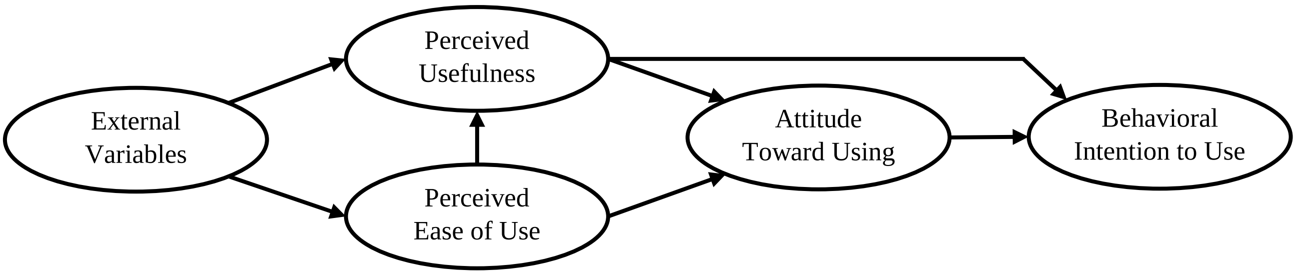

Figure 1: Technology Acceptance Model (after Davis et al., 1989)

When researching the acceptance of innovative technologies, it must be borne in mind that, in addition to their relative advantages over unintelligent or less intelligent devices, they can always entail various risks (Mani & Chouk, 2018). According to the prospect theory of Kahneman and Tversky (1979), possible losses are perceived more clearly than possible gains. The negativity bias theory similarly explains that people give more weight to negative information than comparable positive information when evaluating contexts, objects, or other people (Ito et al., 1998). Therefore, Cenfetelli (2004) recommends taking a person's perceived advantages as well as their inhibitions into account when adopting a technology using a two-factor approach.

Concerns about data privacy that are related to trust building can be understood as an inhibiting factor in technology acceptance. It is demonstrated by McKnight et al. (2011) that a person's trusting beliefs directly result in forming an intention to explore and make deep use of a technology. They concluded this from a survey with 359 MIS students in the USA on their use of the Microsoft Access and Excel programs. Furthermore, Wirtz et al. (2018) emphasize the important role of trust using the example of the acceptance of service robots in their service robot acceptance model, which they developed based on a literature review. Liu et al. (2005) include privacy as a factor of trust in their technology acceptance model: Using the example of an online bookstore, they demonstrated the decisive role of privacy in an experiment and a survey of 258 students and graduates in the USA. Dinev and Hart (2006) use their Extended Privacy Calculus Model to show that in the e-commerce sector, internet privacy concerns have a negative impact on willingness to transact on the internet with data from 369 respondents. Zhou (2011) is able to demonstrate the effects of privacy concerns and trust in the acceptance of location-based services based on a survey of 210 mobile users in China. In the area of social networking services, similar effects are significantly demonstrated by Chang et al. (2017). For this, they conducted twelve interviews with IT & e-commerce experts as well as industry consultants and evaluated a survey of 168 experienced Facebook and LinkedIn users.

With the spread of the smart home concept, respective technologies moved further into the application area of technology acceptance research. Smart home devices represent intelligent devices for the home that can be connected to other devices in a centrally controlled communication network in order to be able to independently fulfill tasks in their function as actuators in response to information from sensors or applications integrated into that network (Balta-Ozkan et al., 2014). In a broader sense, stationary voice assistants can also be viewed as smart home devices. However, they do not fall under the definition used in this paper, since their smart home connection is primarily limited to the control of the actual smart home devices, as is the case with smartphones, smartwatches, and tablets. Concerning technology acceptance, Park et al. (2017) significantly demonstrate all assumptions of the TAM in the acceptance of IoT technologies in the smart home domain based on a survey of 1,057 smart home users. Tereschenko (2020) addresses the acceptance of AI-driven smart home devices by means of an experiment and a survey of 126 people. This work shows that initial trust beliefs play a key role in adoption intention using vacuum robots as an example. Pitardi and Marriott (2020) develop a more comprehensive model for building technology acceptance and trust in the smart home sector, including privacy. Using the example of AI voice assistants, they surveyed 466 users. As a result, they can confirm the hypotheses of the TAM as well, but not the influence of privacy on trust and, thus, the acceptance process. As a result of twelve subsequent in-depth interviews, they are able to explain this result from the fact that privacy concerns are more likely to be directed at the manufacturer or software operator than at the device used. The study by Marikyan et al. (2021) on the acceptance of smart home devices in general shows similar results. After evaluating a survey of 422 current and former smart home users, they are able to confirm the hypotheses of the TAM, as well. However, like Pitardi and Marriott (2020), they do not find any significant influence of privacy on the acceptance process.

As collated above and to our best knowledge, only a few models with regard to technology acceptance have been analyzed in the context of smart home devices. Moreover, mostly, only factors in favor of using the technology are addressed disregarding factors for rejecting it—especially privacy concerns are rarely addressed. Therefore, this paper aims to meet this research need and to make a decisive contribution to technology acceptance research in the domain of smart home technologies.

CONCEPTUAL MODEL

In the field of acceptance research, various impact models for the general prediction of technology acceptance have already been developed and checked as shown above. Among these models, the TAM (Davis, 1986; Davis et al. 1989) is considered one of the most prevalent approaches since a vast number of studies have already confirmed and validated the model. In order to test the main drivers of the technology acceptance of smart home devices, the hypotheses of the TAM (see Figure 1) are also adapted in this study:

H1: *Attitude toward using smart home devices has a positive impact on the behavioral intention to use them.*
H2: *Perceived usefulness of smart home devices has a positive impact on the behavioral intention to use them.*
H3: *Perceived usefulness of smart home devices has a positive impact on the attitude toward using them.*
H4: *Perceived ease of use of smart home devices has a positive impact on the attitude toward using them.*
H5: *Perceived ease of use of smart home devices has a positive impact on their perceived usefulness.*

As in the TAM, the *behavioral intention to use* in the hypotheses of this paper is understood, based on Fishbein and Ajzen (1975), as the subjective probability of a person that it will perform a certain behavior (here: the use of smart home devices). Accordingly, the *attitude toward using* represents the general feeling of a person that the use of a certain technology (here: smart home devices) is advantageous or disadvantageous. The definitions of the two core beliefs of the attitude toward using follow Davis' (1989) definition. *Perceived usefulness* describes the degree to which a person believes that a certain technology is useful in their everyday life, and *perceived ease of use* describes the degree to which that person believes that using this technology is effortless.

The model extensions of TAM2 and TAM3 are not considered in the hypotheses of this paper. The subjective norm is explicitly not included as a variable, as it only has a significant influence on the behavioral intention to use if the use of the technology under consideration is mandatory in the specific context (Lai, 2017; Olbrecht, 2010). This does not apply to the use of smart home devices in a private context. Furthermore, the addition of additional factors from TAM2 and TAM3 would increase the complexity of the research model, which might not lead to any significant advantages compared to the original TAM (Agudo-Peregrina et al., 2014).

In addition to the determinants of use, perceived usefulness and perceived ease of use, trust in the technology also plays a demonstrably decisive role (Warkentin et al., 2017). According to the literature, it is understood as a strong determinant of technology adoption (McKnight et al., 2011; Wirtz et al., 2018). Based on the confirming findings by Wu et al. (2011), the following additional hypotheses are added to the hypotheses H1 to H5 listed above:

H6: *Existing trust in smart home devices has a positive impact on the behavioral intention to use them.*
H7: *Existing trust in smart home devices has a positive impact on the attitude toward using them.*
H8: *Existing trust in smart home devices has a positive impact on their perceived ease of use.*
H9: *Existing trust in smart home devices has a positive impact on their perceived usefulness.*

Trust can be built on a (quasi) interpersonal or systemic level (Lankton et al., 2015). (Quasi) interpersonal trust plays a role when technologies are perceived by users as human-like due to their appearance, their movement, their behavior or possibly even the emotions they express and are therefore humanized (Zlotowski et al., 2014). Since smart home devices have so far hardly had any human-like features, users primarily encounter them with system-related trust (Tereschenko, 2020). A corresponding level of trust is therefore also meant in the hypotheses of this paper. Following the understanding of McKnight et al. (2011) it refers to beliefs that a given technology can perform required tasks (functionality), adequately support one in its use (helpfulness), and function consistently and predictably (reliability).

As recommended by Cenfetelli (2004) in connection with the acceptance of innovative technologies, the research model of this paper follows a two-factor approach. In addition to the introduced driving factors, privacy concerns are covered as an inhibiting factor. This is intended to enable a more holistic view of the technology acceptance of smart home devices. As discovered in prior research, privacy concerns negatively influence trust (Chang et al., 2017; Liu et al., 2005; Zhou, 2011). The combined influences of privacy concerns and trust as extensions of the TAM have only been examined in isolated studies (Marikyan et al., 2021; Pitardi & Marriott, 2020) yet. Based on their research models, the following final hypotheses are added to the hypotheses H1 to H9 listed above:

H10: *Existing privacy concerns about smart home devices have a negative impact on the attitude toward using them.*
H11: *Existing privacy concerns about smart home devices have a negative impact on the trust in them.*

The term *privacy concerns* is used in the hypotheses, taking into account Sweeny and Dooley's (2017) definition of a concern as a person's repeated thoughts focusing on negative events related to the informal autonomy or privacy it can prepare for or which it can foresee.

For clarity, the relationships between the hypotheses are shown graphically in Figure 2. A detailed explanation of the operationalization of the listed constructs follows in the next chapter.

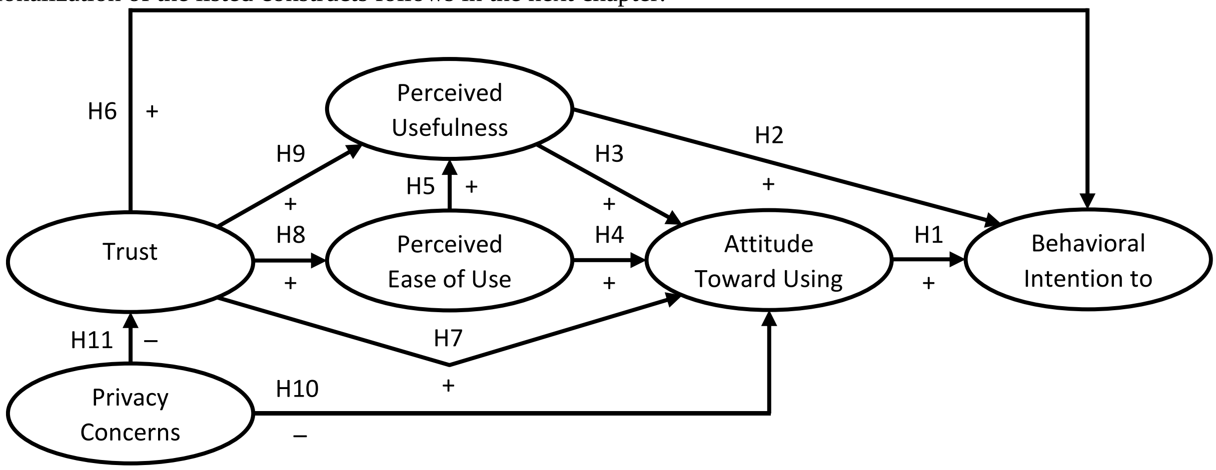

Figure 2: Research model.

METHODOLOGY

Methodological Approach

The empirical study focuses on the German smart home market. Since the full range of functions of smart home devices can usually only be achieved with an internet connection, the total number of internet users living in Germany at the time of the study was defined as the population. In 2021, this included around 66.6 million people aged 14 and over (GIM, 2021). The investigation units were selected in the form of a self-selected sample from the population. As a research method, a quantitative online survey in the form of a computerized self-administered questionnaire was then carried out with them. Due to the selected population, a coverage-related problem could be avoided.

The survey was carried out using smart home thermostats as an application example for examination. This approach was taken to ensure that respondents think of the same device when they hear the generic term 'smart home device' while answering the questions on the variables being studied. Smart home thermostats were chosen as an example device for a variety of reasons: First of all, the chosen definition of smart home devices in this paper applies exactly to them and their basic functional orientation is similar to that of many other devices that fall under that definition. Furthermore, smart home thermostats are highly relevant in the German smart home context. Their purpose relates to two of the three most frequently mentioned reasons for using smart home devices—comfort or quality of life and energy efficiency. Smart home thermostats are among the most used smart home devices (after smart lighting and alarm systems) and have the highest number of planned new purchases (Bitkom, 2020). They can be used in almost any living space and their usability or functionality is sufficiently versatile to ask about the attitude dimensions of the study participants related to them. Especially for examining the variable privacy concerns, smart home thermostats as an exemplary device offer decisive advantages: Many of their functions require a connection to the internet. As long as this exists, there are also privacy risks that can raise privacy concerns among users. Leading manufacturers are promoting online capabilities as the primary value proposition of their smart home thermostats, making an internet connection almost implicit (although not mandatory) when using these devices. Examples of such functions are remote control (via app or voice assistant), geofencing (automation based on user presence in a certain area), weather forecast control, and the use of artificial intelligence to optimize heating.

The empirical data was analyzed by structural equation modeling (SEM). For this, we used the statistics standard software R (version 4.2.0) as well as the package lavaan (version 0.6-11).

Operationalization

The operationalization of the constructs is based on scales from various preceding studies that are already empirically shown to be reliable. All items are originally in English. Since we aimed at participants from Germany, the survey is in German such that the items had to be translated into German. Due to the different study orientations, the composition of the item blocks was mostly not suitable for the research interest of this paper. Therefore, items from different studies were combined and adapted to the context of smart home thermostats.

In total, 18 items regarding six constructs were used in the survey. Table 1 shows the English versions of these items. The characteristics of behavioral intentions and attitude dimensions of the survey participants were measured using five-point Likert scales (*do not agree at all, tend not to agree, neither, tend to agree*, and *fully agree*).

Table 1: Operationalization of the examined constructs

Construct	Code	Indicator	Item	Source
Behavioral intention to use	**BI**	*Planned…* …use	*I would…* …like to use smart home thermostats.	Tereschenko (2020)
		…frequency …recommendation	…use smart home thermostats as much as possible. …recommend smart home thermostats to other people.	Park et al. (2017)
Attitude toward using	**AU**	Incentive Positive feelings Positive opinion	The thought of using smart home thermostats is appealing to me. I have generally positive feelings toward using smart home thermostats. Overall, I think using smart home thermostats is a good idea.	Pitardi & Marriott (2020)
Perceived usefulness	**PU**	*Perceived…* …service or information provision …comfort …lifestyle fit	*I think…* …smart home thermostats would provide me with useful services and information. …it would be comfortable for me to use smart home thermostats. …smart home thermostats would be useful for my lifestyle.	Park et al. (2017)
Perceived ease of use	**PE**	*Perceived…* …learnability of use …daily usability …improvement in use	*I think it would be easy for me to…* …learn how to use smart home thermostats. …use smart home thermostats in everyday life. …become skillful at using smart home thermostats.	Pitardi & Marriott (2020)
(System-like) Trust	**ST**	*Attributed…* …functionality …reliability	*I think smart home thermostats…* …have the right properties and features for my needs. …are very safe and reliable.	Tereschenko (2020)
		…trustworthiness	…are trustworthy.	Pitardi & Marriott (2020)
Privacy concerns	**PC**	*Concerns about…* …amount of data …data privacy	*I have concerns about…* …the amount of information… …the confidentiality of the information…	Pitardi & Marriott (2020)
		…manufacturer data usage	…the manufacturer's use of the information… *…that smart home thermostats collect about me and my interactions with them.*	Dinev & Hart (2006)

Before the questionnaire was finally rolled out, a number of pre-tests were carried out. In addition to a systematic analysis of the selected items according to Faulbaum et al. (2009), cognitive interviews were also conducted with 15 test participants using the methods of probing, confidence rating, and thinking-aloud. The feedback from those pretests made it clear that the test participants found the questionnaire to be very understandable, intuitive, and appealing. Furthermore, various suggestions for improvement were obtained, which were also implemented after weighing up possible advantages and disadvantages.

Sample

The online survey was conducted from the 14th until the 27th of March, 2022. After those two weeks of data collection, we gathered 427 data sets of which 353 (82.67%) were complete. From those 353, we excluded 27 data sets due to zero response variance (eight cases of straight liners) or a response time of less than half of the median, i.e., less than 1:50 min. (median response time: 3:40 min.; 23 cases of speeders—partly overlapping with straight liners). Consequently, we could gather a sample of 324 valid data sets.

In the sample, around two-thirds (65.1%) have experience with smart home appliances (34.3% no experience; 0.6% not specified). 44.1% of the respondents (or 65.1% of the smart home users) have been using smart home appliances for at most three years, whereas only 13.9% have five years of experience or more. The comparison of the sample with the German population of web users in Table 2 shows that the sample is 10 years younger (32 vs. 42 years), slightly more female (54% vs. 50%), and substantially better educated (86% vs. 38% high education level) than the overall German population.

Table 2: Comparison sample and German population of web users

	Age	**Sex**		**Education**		
	Avg. (Years)	**Female**	**Male**	**Low**	**Medium**	**High**
Sample	32	54%	44%	1%	14%	86%
Germany	42	50%	50%	30%	32%	38%

Sources: GIM (2021) for Age, Sex; Initiative D21 (2022) for Education.

Reliability and Validity

Regarding the reliability of the empirical measurement, all latent constructs obtain a Cronbach's alpha over the threshold of 0.7. Thus, the reliability can be confirmed based on a "good" to "excellent" consistency reaching from 0.781 to 0.935 (see Table 3).

Table 3: Reliability and validity indicators

	BI	**AU**	**PU**	**PE**	**ST**	**PC**
Cronbach's alpha	0.914	0.917	0.858	0.933	0.781	0.935
Consistency *(after Taber, 2018)*	"strong"	"strong"	"good"	"excellent"	"good"	"excellent"
Avg. variance extracted (AVE)	0.786	0.796	0.675	0.826	0.598	0.833
Max. squared correlation	0.922	0.953	0.953	0.148	0.632	0.381
Max. HTMT ratio	0.910	0.938	0.938	0.380	0.859	0.533

The confirmatory factor analysis shows an average variance extracted (AVE) of 0.598 to 0.833, i.e., all factors are above the threshold of 0.5, which indicates convergent validity. Concerning discriminatory validity, the Fornell-Larcker test (1981) requires that the AVE is larger than the maximal squared correlation (max $r_{i,j}^2 \; \forall \; I \neq j$), which is not the case for BI, AU, and PU due to their very high correlations (0.939, 0.960, and 0.976) (see Table 5). PE and PC pass the Fornell-Larcker test completely, whereas ST does not meet the requirement technically, but is qualitatively acceptable. Another more advanced discriminatory validity assessment is the Heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al., 2015) which should be at least below 0.9 or, more conservatively, below 0.85. These calculations confirm the discriminatory insufficiencies of BI, AU, and PU that we will account for in the discussion. For ST, the HTMT ratio of 0.859 is below 0.9 and almost below 0.85, which shows an acceptable discriminatory validity.

RESULTS

In this section, we present the results of the descriptive and inductive statistics from the 324 complete data sets in the survey.

Table 4: Descriptive statistics (summated multi-item scale scaled to 1 – 5)

	BI	**AU**	**PU**	**PE**	**ST**	**PC**
Min	1.000	1.000	1.000	1.000	1.000	1.000
1st Quartile	3.333	3.667	3.333	4.000	3.333	2.000
Median	4.000	4.000	4.000	4.667	3.667	3.000
3rd Quartile	4.333	4.667	4.333	5.000	4.000	4.000
Max	5.000	5.000	5.000	5.000	5.000	5.000
Mean	3.746	3.900	3.825	4.400	3.645	3.104
SD	1.016	0.968	0.943	0.765	0.774	1.175
CoV	27.1%	24.8%	24.7%	17.4%	21.2%	37.9%

Table 4 shows the results of the descriptive statistics of the six latent factors. For illustration and interpretation purposes, we draw on the sum of the respective items here (scaled to 1 – 5). In the remainder of the paper, we use the factor scores resulting from the SEM, though. As the data shows, all constructs comprise the full spectrum of possible answers with a minimum of 1 (answering all items with complete disagreement) and a maximum of 5 (answering all three items with complete agreement). PE has the highest average score (4.400) with the smallest coefficient of variation (CoV; 17.4%), which is an indicator that smart home technology has achieved apprehended usability. PU (3.825), AU (3.900), and BI (3.746) have less but also relatively high approval scores. With ST (3.645) and especially PC (3.104), the respondents are expectedly more skeptical, albeit those two constructs also receive a fair amount of agreement.

In terms of bivariate correlation (see table 5; now based on factor scores from the SEM), the data shows a very high pairwise correlation coefficient between BI, AU, and PU (0.939 – 0.976) being almost perfectly positively correlated. PE shows a moderate positive effect on each variable (0.306 – 0.385) except for PC, which is substantially negatively correlated (-0.617). Generally, PC shows negative effects on the other factors (-0.617 – -0.242). Except for PC, ST is statistically positively associated with the other variables with a moderate effect on PE (0.331) and even a large effect on PU, AU, and BI (0.708 – 0.795).

Table 5: Correlation matrix (based on factor scores)

	BI	**AU**	**PU**	**PE**	**ST**	**PC**
BI	1	0.939	0.960	0.306	0.708	-0.302
AU		1	0.976	0.385	0.795	-0.348
PU			1	0.357	0.739	-0.297
PE				1	0.331	-0.242
ST					1	-0.617
PC						1

To check for normality in the SEM data, we calculated Mardia's multivariate skew and kurtosis statistics: the data possess a significant positive skewness (right-skewed) as well as an excess kurtosis (leptokurtic)—both with $p < 0.0001$—indicating non-normality (which is also hinted graphically by the Q-Q plot; not depicted). Therefore, we computed the SEM with the estimation method "Maximum Likelihood Mean Adjusted" (MLM) applying a maximum likelihood approach and a scaling of the chi-square statistics according to Satorra-Bentler (2001) to adjust for non-normality in the fitness measures. The fitness measures (with said scaling) are shown in Table 6 along with suggested cutoff values (after Schermelleh-Engel et al., 2003) specifying the acceptability of the SEM. All fitness measures reach the suggested criteria except for the NNFI (Non-normed Fit Index), which shows a slight underfitting (0.943 < 0.95) whereas the NFI (Normed Fitness index) is adequate (0.917 ≥ 0.9). However, the criterion of ≥ 0.9 was originally also applied for the NNFI (Hu & Bentler, 1999) which would have been satisfied in this model. In summarizing, the model manifests adequate fit properties.

Table 6: Fit of the SEM (Satorra-Bentler corrected)

Measure	**$\chi 2$ / df**	**RMSEA**	**p-value (RMSEA ≤ 0.05)**	**SRMR**	**CFI**	**NFI**	**NNFI**
Value	2.129	0.059	0.028	0.082	0.954	0.917	0.943
Cutoff	≤ 3	≤ 0.08	≤ 0.05	≤ 0.1	≥ 0.95	≥ 0.9	≥ 0.95

Note: df = degrees of freedom, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual, CFI = Comparative Fit Index, NFI = Normed Fit Index, NNFI = Non-normed Fit Index. Cutoff values taken from Schermelleh-Engel et al. (2003).

Table 7 shows the results of the estimation of the SEM path coefficients as well as their significance. Regarding the paths towards BI, PU has a particularly high effect ($\beta = 0.803$) that is also very highly significant ($p < 0.001$). On the other hand, ST does not seem to influence BI ($p = 0.914$). For AU, the data is inconclusive as the 95% confidence interval (CI) of β reaches from -0.021 to 0.667 ($p = 0.066$). The overall R^2 of BI is 85.2% explained variance, which is a substantial effect size after Chin (1998). The path model of AU also has a substantial effect size with an R^2 of 90.4%. The paths of PU → AU ($\beta = 1.037$; $p < 0.001$) and ST → AU ($\beta = 0.377$; $p < 0.01$) show a very strong evidence in particular. In contrast, there is effectively no evidence supporting the influence of PE and PC on AU ($p = 0.192$ and $p = 0.652$, respectively). For PU (with a moderate effect based on a R^2 of 46.7%), the influence factors PE ($\beta = 0.142$; $p < 0.01$) and especially ST ($\beta = 0.887$; $p < 0.001$) indicate a strong relationship with PU. The path model of PE with only one explanatory variable has a limited explained variance ($R^2 = 9.1\%$, very weak effect size). However, the only path of this sub-model, ST → PE, is highly significant ($\beta = 0.434$; $p < 0.001$). Finally, the PC → ST shows very strong evidence for a negative relationship ($\beta = -0.276$; $p < 0.001$) that can explain 32.6% of the variance of ST and is a weak to moderate effect.

After analyzing the direct effects of the respective path sub-models, we computed the indirect effect as well as the total effect (combining indirect and direct effect) on BI in the overall model for every other factor—as shown in Table 8.

Table 7: Results of the SEM

Paths towards BI (R^2: 0.852)	**Coefficient**	**95% CI**	**Std. Error**	**p-value**
AU → BI	0.323	-0.021 – 0.667	0.176	0.066
PU → BI	0.803	0.381 – 1.225	0.215	0.000
ST → BI	-0.011	-0.213 – 0.191	0.103	0.914
Paths towards AU (R^2: 0.904)	**Coefficient**	**95% CI**	**Std. Error**	**p-value**
PU → AU	1.037	0.874 – 1.2	0.083	0.000
PE → AU	0.055	-0.028 – 0.139	0.042	0.192
PC → AU	0.015	-0.051 – 0.082	0.034	0.652
ST → AU	0.377	0.164 – 0.59	0.109	0.001
Paths towards PU (R^2: 0.467)	**Coefficient**	**95% CI**	**Std. Error**	**p-value**
PE → PU	0.142	0.041 – 0.243	0.052	0.006
ST → PU	0.887	0.673 – 1.1	0.109	0.000
Paths towards PE (R^2: 0.091)	**Coefficient**	**95% CI**	**Std. Error**	**p-value**
ST → PE	0.434	0.253 – 0.614	0.092	0.000
Paths towards ST (R^2: 0.326)	**Coefficient**	**95% CI**	**Std. Error**	**p-value**
PC → ST	-0.276	-0.342 – -0.211	0.033	0.000

Since AU has no indirect connection to AU, it only comprises its direct effect (see above, $\beta = 0.323$; $p = 0.066$) which is logically the same as its total effect. Whereas PU's indirect effect is inconclusive yet (95% CI: -0.013 – 0.683; $p = 0.059$), its total effect adding the direct influence is highly evident ($\beta = 1.138$; $p < 0.001$). PE as well as PC only consists of indirect effects that show a small positive and medium negative, but statistically significant, impact on BI ($\beta = 0.179$; $p < 0.01$ and $\beta = -0.326$; $p < 0.001$). Eventually, while ST has effectively no evidence of directly influencing BI ($\beta = -0.011$; $p = 0.914$), its indirect effect strongly suggests a significant mediated relationship ($\beta = 1.208$; $p < 0.001$) leading to the strongest total effect in the SEM ($\beta = 1.197$; $p < 0.001$).

Table 8: Indirect and Total Effects on BI

	Indirect Effect				***Total Effect***			
	Coefficient	**95% CI**	**Std. Error**	**p-value**	**Coefficient**	**95% CI**	**Std. Error**	**p-value**
AU	--	--	--	--	0.323	-0.021 – 0.667	0.176	0.066
PU	0.335	-0.013 – 0.683	0.178	0.059	1.138	0.961 – 1.315	0.090	0.000
PE	0.179	0.066 – 0.293	0.058	0.002	0.179	0.066 – 0.293	0.058	0.002
ST	1.208	0.916 – 1.501	0.149	0.000	1.197	0.937 – 1.458	0.133	0.000
PC	-0.326	-0.404 – -0.247	0.040	0.000	-0.326	-0.404 – -0.247	0.040	0.000

DISCUSSION AND CONCLUSION

Discussion of the Hypotheses

The outcomes of the eleven hypotheses based on the empirical study are shown in Table 9.

Table 9: Hypotheses Evaluation

H.	**Path**	**Sig.**	**Conclusion**	**H.**	**Path**	**Sig.**	**Conclusion**
H1	AU → BI	°	*inconclusive*	H7	ST → AU	***	*accepted*
H2	PU → BI	***	*accepted*	H8	ST → PE	***	*accepted*
H3	PU → AU	***	*accepted*	H9	ST → PU	***	*accepted*
H4	PE → AU		*rejected*	H10	PC → AU		*rejected*
H5	PE → PU	**	*accepted*	H11	PC → ST	***	*accepted*
H6	ST → BI		*rejected*	*significance codes ° < 0.1, * < 0.05, ** < 0.01, *** < 0.001*			

Firstly, the hypotheses H1–H5 have addressed general technology acceptance variables based on the TAM (Davis, 1989). The influence of AU could not be shown on a 0.05 significance level. Since the p-value is a continuous measurement of evidence, the p-value of 0.066 is suggestive, but not conclusive (Murtaugh, 2014). As meta-studies on technology acceptance such as Blut et al. (2016) or Yousafzai et al. (2007) have shown, the connection between AU and BI is usually highly significant—the correlation of 0.939 in this study also indicates this close statistical connection. Nevertheless, BI, AU, and PU have failed the Fornell-Larcker test and the HTMT ratio threshold showing a lack of discriminatory validity, i.e., the measurements of the constructs are not sufficiently distinct to differentiate between those three variables. This fact may very likely interfere with the conclusion, since H2 (PU → BI) and H3 (PU → AU) are very highly significant and, thus, accepted. Regarding the perceived ease of use, the data indicates a significant positive relation between PE and PU such that H5 is accepted. H4 (PE → AU) is rejected due to lacking significance, though. In this regard, the meta-study of Yousafzai et al. (2007) shows that 18% of the 52 analyzed TAM studies did not find a significant positive correlation between PE and AU. In this study, the items of PE have a very easy item difficulty (the average score of PE is 4.4 out of 5 with item difficulties between 87.59% and 88.64%). Item difficulties above 80% lead to the so-called ceiling effect that does not allow for discrimination between subjects with high approval (Austin & Brunner, 2003) which might have interfered with our analysis despite the excellent internal consistency of the factor. Nevertheless, PE shows a highly significant total effect on BI due to the moderation via PU.

Secondly, the hypotheses H6–H9 have addressed the impact of ST on the factors BI (H6), AU (H7), PE (H8), and PU (H9). H6 could not be confirmed despite the very high correlation of 0.708 between ST and BI. Since ST also influences AU and PU, the lack of discrimination once again might interfere with this result. However, the data shows a very high significance regarding AU, PE, and PU such that H7, H8, and H9 can be confirmed. Previous work studying the effects of ST observed similar outcomes. For instance, Wu et al. (2011) confirmed in their meta-study the significant influence of ST on AU, PE, and PU. Moreover, they also found a significant weighted mean effect size of 0.527 in the ST–BI relationship with a failsafe N of 196,63. This further supports the assumption above on the interference of the lack of discrimination with the results regarding H6.

Thirdly, the two final hypotheses H10–H11 have addressed the role of PC. Different than expected, PC only showed an traceable influence on ST and none on AU. H10 has therefore to be rejected while H11 can be accepted. This outcome is contrary to the study by Pitardi and Marriott (2021) regarding voice assistants. They found an influence of PC on AU, but none on trust. However, their operationalization of trust primarily related to the communication of the voice assistant and largely corresponded to the (quasi-)interpersonal trust as described by Mayer et al. (1995) and McKnight et al. (2002). Against this background, the result that concerns about more technical data privacy do not affect (quasi) interpersonal trust in a technology seems plausible. In contrast, the investigation within the scope of this paper did not have the (quasi) interpersonal trust, but the system-related trust according to McKnight et al. (2011) to the subject. The proven mediation of the influence of PC via ST on AU could explain why Pitardi and Marriott (2021) perceived this influence of PC on AU as direct without considering ST. Regarding the negative effect of PC on ST, the results of this paper show very supportive evidence in accordance with previous studies such as Chang et al. (2017), Zhou (2011), and Liu et al. (2005). Concerning the moderated effect on BI, PC shows a substantial negative indirect effect of -0.326 on BI, mainly moderated by ST.

Practical Implications

For practitioners from the smart home domain, we can recommend three key aspects based on our findings:

Firstly, smart home devices should be designed for maximum perceived usefulness and trust. Regarding the former, product designers should think about optimizing service or information provision, comfort, and lifestyle fit towards the user. Regarding the latter, the indicators of functionality, reliability, and trustworthiness are relevant in this context.

Secondly, as the descriptive statistics and the easy item difficulties have shown, the maturity in terms of perceived ease of use appears to be relatively high. Furthermore, the total effect on the behavioral intention to use has been the lowest of all analyzed variables. Therefore, perceived ease of use of smart home devices should not be given too much attention during product development.

Thirdly, the smart home manufacturers should highlight trust and privacy concerns characteristics in their advertisements and customer communication. As we have shown, these two factors have a substantial positive or negative, respectively, impact on the behavioral intention to use. Simultaneously, both issues are easy to address within the customer address—in contrast to perceived usefulness which more heavily relies on physical features than on comprehensive dispositions.

Limitations

The generalizability of our findings is subject to certain limitations in our research design, the available literature, and our empirical measurement:

Addressing our research design, we have chosen smart home thermostats as an exemplary technology. This may not be representative of smart home technologies in general. Furthermore, to assure an informed response, we have provided basic information about smart thermostat features by an introductory text at the beginning of the survey. Although potential users might also inform themselves before their purchase, the given information might have biased the responses in any manner. To keep this risk as little as possible, we tried to follow and imitate real product information texts.

Concerning the available literature, the literature search appeared to be challenging because smart home devices are relatively young technologies that have not been researched extensively from a technology acceptance perspective yet.

Regarding the empirical measurement, we must limit our findings to the German context since the survey was not only written in German but also exclusively conducted among German residents. As we have argued, the average respondent in our sample is a little younger but by far more formally educated than the average German online user. Finally, the statistical analysis of the results revealed two weaknesses of the data: Firstly, the constructs of BI, AU, and PU fail to establish a sufficient discriminatory validity leaving some uncertainty about the outcomes of their direct interactions—even though the goal of this study is not the replication of these core TAM construct. Secondly and lastly, the measurement of PE shows very easy item difficulties leading to a ceiling effect that hinders the discrimination between subjects with high PE.

Conclusion and Future Work

In the field of acceptance research, various models for the general prediction of technology acceptance have been established. However, trust and privacy concerns have been hardly taken into account yet—especially in the context of smart home devices. Nevertheless, our results demonstrate a very strong positive effect of trust on smart home technology acceptance as well as a moderate negative impact of privacy concerns showing the relevance of these factors.

Based on the findings, this paper provides three main theoretical contributions: firstly, the paper conceptionally adds the special relationships of trust and privacy concerns with the determinants of use to the technology acceptance theory in the context of smart home devices. Secondly, the study provides empirical evidence for those relationships and can show that they can play an important role in technology acceptance. Thirdly, this work studies smart home adoption based on the example of smart thermostats and, by doing so, generates original insights and explanations of the phenomenon.

Future work will be to further validate the theoretical contributions made in this paper. To achieve this, investigations have to be carried out using a more representative sample and with various smart home devices as a basis for the survey. For an even broader understanding, additional investigations need to be conducted in different countries and different contexts of use. Furthermore, the specific drivers of users' trust in smart home devices need to be identified. This would give manufacturers and software operators more substantiated insights on how to develop and advertise their smart home devices accordingly in order to achieve higher user acceptance.

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APPENDIX:
Questionaire

10% ausgefüllt

Zum Einstieg starten wir mit einer allgemeinen Frage zu Ihrem **bisherigen Kontakt mit Smart-Home-Geräten**.

Smart-Home-Geräte sind im weiteren Sinne *intelligente* Geräte für den *Heimbereich*, die sich mit anderen Geräten in einem *Funknetzwerk* verbinden lassen und dadurch *ferngesteuert*, *geplant* oder als *eigenständige* Reaktion auf Umweltreize *Aufgaben* erfüllen können.

In welchen Anwendungsbereichen nutzen Sie bereits Smart-Home-Geräte?

- ☐ Energiemanagement *(z. B. Beleuchtung, Heizung)*
- ☐ Gebäude- & Wohnsicherheit *(z. B. Alarmanlage, Rauchmelder)*
- ☐ Entertainment & Kommunikation *(z. B. TV- und Audiogeräte)*
- ☐ Hausautomation & Komfort *(z. B. Rolläden, Staubsauger)*
- ☐ Gesundheit & Alltagsassistenz *(z. B. Sturzmonitor, Hausnotruf)*
- ☐ Ich nutze keine Smart-Home-Geräte.

Figure 3: Question module on contact to smart home devices.

20% ausgefüllt

Nun bitte ich Sie, sich den folgenden Text aufmerksam durchzulesen.

Er enthält grundsätzliche **Informationen über smarte Heizungsthermostate**.

Die Fragen auf den nachfolgenden Seiten werden sich auf diese Technologie beziehen.

Wenn Sie fertig sind, klicken Sie bitte auf „Weiter".

Smart-Home-Thermostate

Nutzen

- Hohe Genauigkeit und viele Zusatzfunktionen
- Senkung des Energieverbrauchs und Erhöhung des Wohnkomforts durch Automatisierung der Heizvorgänge

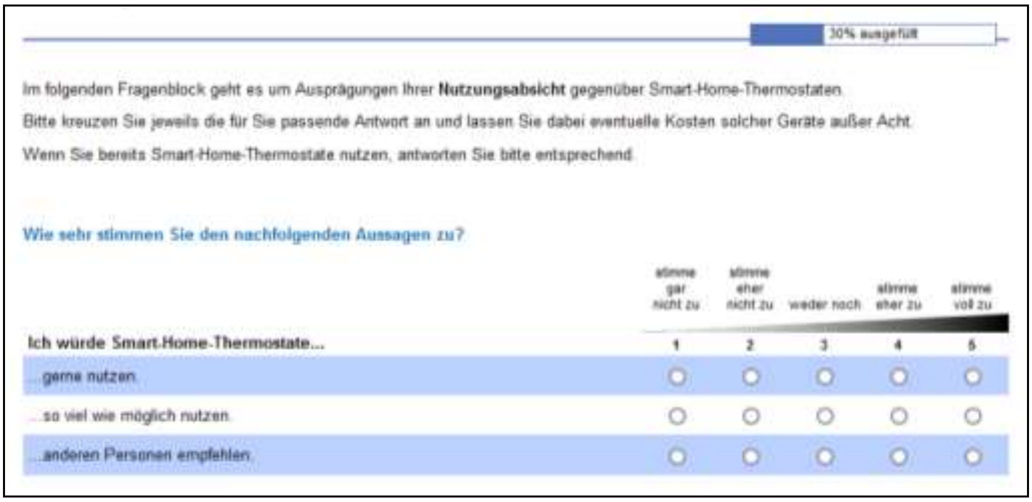
Generelle Funktionen

- Heizverhalten basiert weitgehend auf vorab eingestellten raumindividuellen Zeitplänen und erfasster Raumtemperatur
- Verschiedene Sensoren ermöglichen situative Anpassung des Heizverhaltens außerhalb der Zeitpläne bei anhaltender Raumnutzung (Helligkeit, Bewegung, Geräusch etc.) oder geöffnetem Fenster

Internet-Funktionen

- Fernsteuerung per Smartphone, Sprachassistent etc. (auch manuelle Bedienung möglich)
- Automatisches An- und Abschalten je nach Anwesenheit der Bewohner*innen
- Einbezug der Wettervorhersage in das Heizverhalten
- Online-Datenspeicherung für Statistiken über Heizverhalten, Energieverbrauch etc.
- Verbindung zum Hersteller zwecks Updates, Produktentwicklung, individuellem Marketing etc.
- Künstliche Intelligenz zur Heizoptimierung auf Basis erfasster Daten über die Raumnutzungsgewohnheiten der Bewohner*innen

Figure 4: Information text on smart home devices.



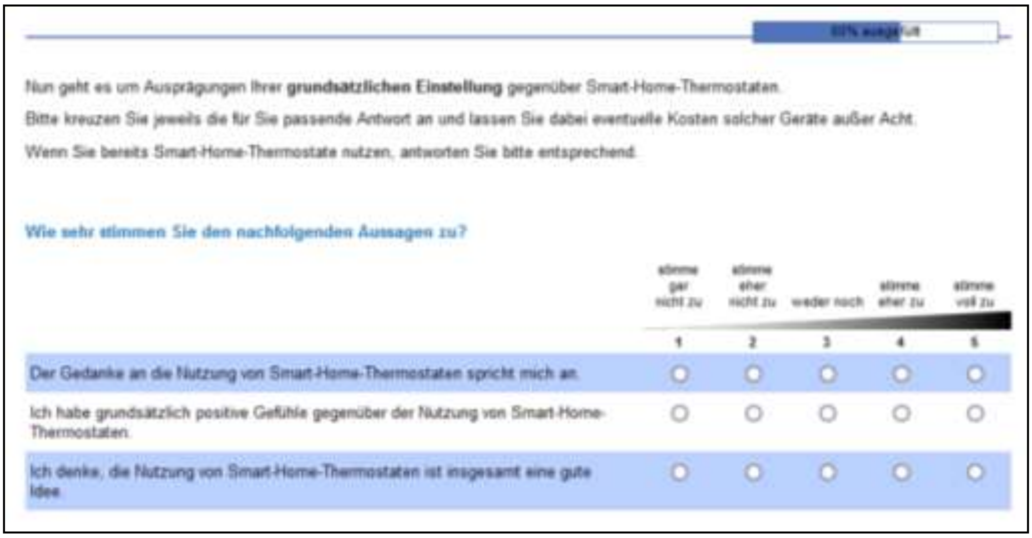
30% ausgefüllt

Im folgenden Fragenblock geht es um Ausprägungen Ihrer **Nutzungsabsicht** gegenüber Smart-Home-Thermostaten.
Bitte kreuzen Sie jeweils die für Sie passende Antwort an und lassen Sie dabei eventuelle Kosten solcher Geräte außer Acht.
Wenn Sie bereits Smart-Home-Thermostate nutzen, antworten Sie bitte entsprechend.

Wie sehr stimmen Sie den nachfolgenden Aussagen zu?

	stimme gar nicht zu	stimme eher nicht zu	weder noch	stimme eher zu	stimme voll zu
Ich würde Smart-Home-Thermostate...	1	2	3	4	5
...gerne nutzen.	○	○	○	○	○
...so viel wie möglich nutzen.	○	○	○	○	○
...anderen Personen empfehlen.	○	○	○	○	○

Figure 5: Question module on behavioral intention to use.



Nun geht es um Ausprägungen Ihrer **grundsätzlichen Einstellung** gegenüber Smart-Home-Thermostaten.
Bitte kreuzen Sie jeweils die für Sie passende Antwort an und lassen Sie dabei eventuelle Kosten solcher Geräte außer Acht.
Wenn Sie bereits Smart-Home-Thermostate nutzen, antworten Sie bitte entsprechend.

Wie sehr stimmen Sie den nachfolgenden Aussagen zu?

	stimme gar nicht zu	stimme eher nicht zu	weder noch	stimme eher zu	stimme voll zu
	1	2	3	4	5
Der Gedanke an die Nutzung von Smart-Home-Thermostaten spricht mich an.	○	○	○	○	○
Ich habe grundsätzlich positive Gefühle gegenüber der Nutzung von Smart-Home-Thermostaten.	○	○	○	○	○
Ich denke, die Nutzung von Smart-Home-Thermostaten ist insgesamt eine gute Idee.	○	○	○	○	○

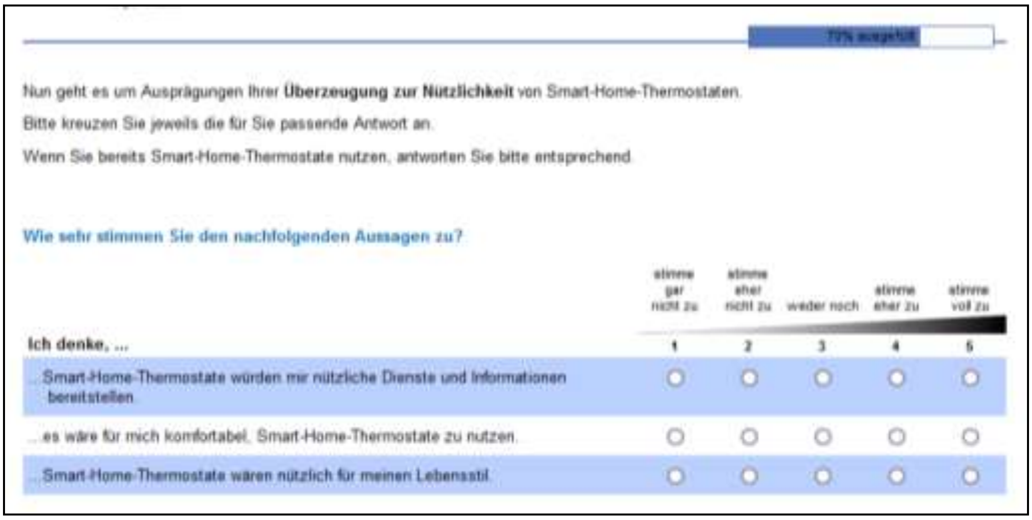
Figure 6: Question module on attitude toward using.

Nun geht es um Ausprägungen Ihres **Vertrauens** gegenüber Smart-Home-Thermostaten.
Bitte kreuzen Sie jeweils die für Sie passende Antwort an.

Wie sehr stimmen Sie den nachfolgenden Aussagen zu?

	stimme gar nicht zu	stimme eher nicht zu	weder noch	stimme eher zu	stimme voll zu
Ich denke, Smart-Home-Thermostate...	1	2	3	4	5
...besitzen die passenden Eigenschaften und Funktionen für meine Anforderungen.	○	○	○	○	○
...sind sehr sicher bzw. verlässlich.	○	○	○	○	○
...sind vertrauenswürdig.	○	○	○	○	○

Figure 7: Question module on trust.


70% ausgefüllt

Nun geht es um Ausprägungen Ihrer **Überzeugung zur Nützlichkeit** von Smart-Home-Thermostaten.

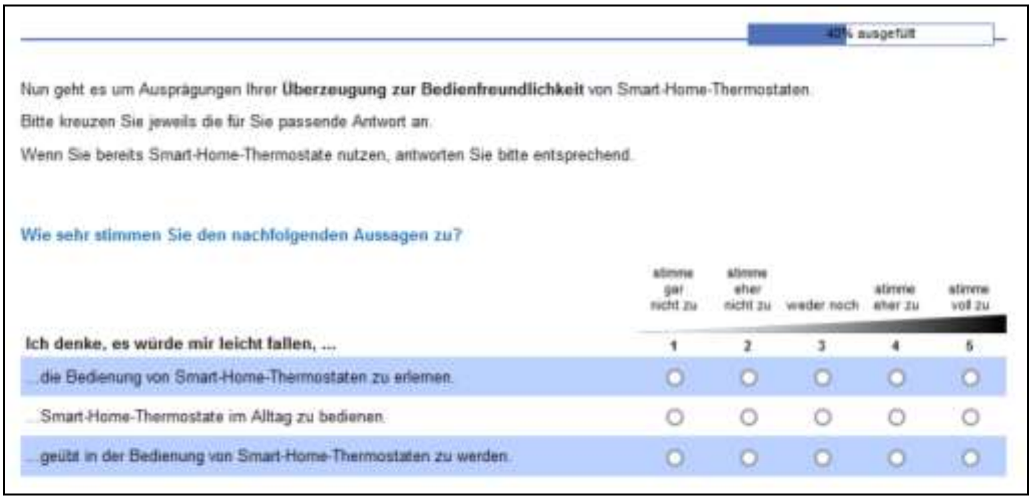
Bitte kreuzen Sie jeweils die für Sie passende Antwort an.

Wenn Sie bereits Smart-Home-Thermostate nutzen, antworten Sie bitte entsprechend.

Wie sehr stimmen Sie den nachfolgenden Aussagen zu?

Ich denke, ...	stimme gar nicht zu 1	stimme eher nicht zu 2	weder noch 3	stimme eher zu 4	stimme voll zu 5
Smart-Home-Thermostate würden mir nützliche Dienste und Informationen bereitstellen.	○	○	○	○	○
...es wäre für mich komfortabel, Smart-Home-Thermostate zu nutzen.	○	○	○	○	○
...Smart-Home-Thermostate wären nützlich für meinen Lebensstil.	○	○	○	○	○

Figure 8: Question module on perceived usefulness.


40% ausgefüllt

Nun geht es um Ausprägungen Ihrer **Überzeugung zur Bedienfreundlichkeit** von Smart-Home-Thermostaten.

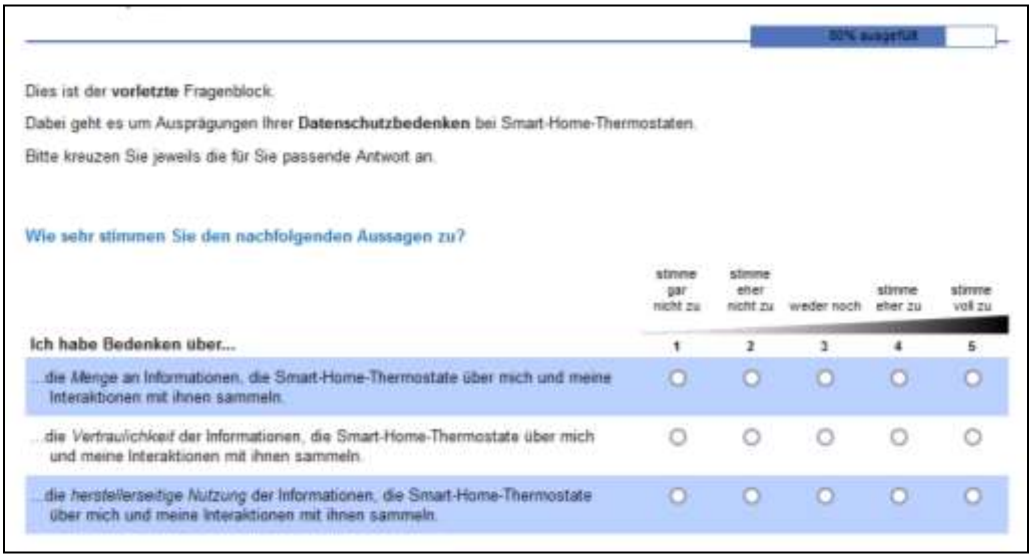
Bitte kreuzen Sie jeweils die für Sie passende Antwort an.

Wenn Sie bereits Smart-Home-Thermostate nutzen, antworten Sie bitte entsprechend.

Wie sehr stimmen Sie den nachfolgenden Aussagen zu?

Ich denke, es würde mir leicht fallen, ...	stimme gar nicht zu 1	stimme eher nicht zu 2	weder noch 3	stimme eher zu 4	stimme voll zu 5
...die Bedienung von Smart-Home-Thermostaten zu erlernen.	○	○	○	○	○
...Smart-Home-Thermostate im Alltag zu bedienen.	○	○	○	○	○
...geübt in der Bedienung von Smart-Home-Thermostaten zu werden.	○	○	○	○	○

Figure 9: Question module on perceived ease of use.


80% ausgefüllt

Dies ist der **vorletzte** Fragenblock.

Dabei geht es um Ausprägungen Ihrer **Datenschutzbedenken** bei Smart-Home-Thermostaten.

Bitte kreuzen Sie jeweils die für Sie passende Antwort an.

Wie sehr stimmen Sie den nachfolgenden Aussagen zu?

Ich habe Bedenken über...	stimme gar nicht zu 1	stimme eher nicht zu 2	weder noch 3	stimme eher zu 4	stimme voll zu 5
...die *Menge* an Informationen, die Smart-Home-Thermostate über mich und meine Interaktionen mit ihnen sammeln.	○	○	○	○	○
...die *Vertraulichkeit* der Informationen, die Smart-Home-Thermostate über mich und meine Interaktionen mit ihnen sammeln.	○	○	○	○	○
...die *herstellerseitige Nutzung* der Informationen, die Smart-Home-Thermostate über mich und meine Interaktionen mit ihnen sammeln.	○	○	○	○	○

Figure 10: Question module on privacy concerns