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INTRUSIVE SMART HOME ASSISTANTS: AN EXPLORATORY STUDY AND SCALE DEVELOPMENT

Research in Progress

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Abstract

Despite having many useful capabilities, more recently smart home assistants (SHAs) have also raised negative feelings and doubts which may cause resistance among potential users. However, current research has neither examined SHAs from the perspective of resistance nor its specific drivers (inhibitors). We address this gap and adopt a mixed-method research design with two studies that build on each other. Study 1 (N=10) elicits the belief structures underlying resistance to SHAs. Study 2 (N=276) builds on these findings and delves deeper into the understanding of one novel identified inhibitor, namely “perceived intrusion”, by taking initial strides towards creating a measurement instrument. Our results contribute to the previously under-researched “dark side” of smart consumer IT by examining the phenomenon of resistance. This way, we hope to inspire future research to expand on our findings, as well as apply our measurement instrument in other smart product contexts.

Keywords: Smart product, Resistance, Scale development, Mixed-method

1 Introduction

In recent years, smart home assistants such as the Amazon Echo or the Google Home Speaker have become very popular and contributed to the digitization of individuals (Touzani et al. 2018; Benlian et al. 2020; Turel et al. 2020). Smart home assistants (hereinafter SHA) are voice-controlled and function as personal “helpers” for the smart home environment that support users through various skills or actions. To this end, they can respond to user queries, connect with other devices and evolve via machine learning capabilities (Mallat et al. 2017; Benlian et al. 2020). Belonging to the class of smart products, SHAs can be considered as cyber-physical bundles comprising a material layer containing hardware properties such as microphone arrays, displays, and speakers (e.g., Amazon Echo device), and a virtual layer consisting of software for virtual assistance (e.g., Alexa) (Raff et al. 2020). While most SHAs operate through a stand-alone physical device (i.e., a speaker), SHAs may also be embedded into everyday objects such as lamps or stoves, as well as into structural components of the home such as walls and ceilings (e.g., Klipsch Amazon Echo multi-room speaker system with in-ceiling or in-wall mount). While SHAs have long been merely a gimmick, they are now taking on an increasingly important role, both from a user and practitioner perspective. For users, SHAs increase everyday convenience by offering a variety of customized services (Knote et al. 2021). For practitioners, SHAs are a crucial interface technology as they have the potential to significantly enhance datafication, facilitate the continuous delivery of personalized services, and ultimately, drive the emergence of the smart home as a whole (Beverungen et al. 2019; Turel et al. 2020; Schulz et al. 2021). Put differently, the successful adoption of SHAs can be a tipping point, as this leads to up- and cross-selling of other connected smart products that drive the smart home overall, while their rejection can significantly hinder this development.

However, despite their increasing importance and benefits, more recently SHAs have also raised more and more negative feelings and doubts, as they are increasingly perceived as scary, risky, or invasive. For example, SHAs were among the products deemed most creepy, safety hazardous, and privacy-invasive on the Mozilla Foundation's popular buyer's guide which allows consumers to rank various smart products based on perceived concerns (Mozilla 2022). In addition, recent media reports about incidents of unwanted eavesdropping, recording, and sending of private conversations, or poor skill safety have further stoked reservations on the part of consumers (e.g., Lynskey 2019; Winder 2021). Thus, the idea of an SHA that is always listening and whose decision and recommendation logic is not completely transparent may appear more and more like a spooky nightmare rather than a great vision (Lynskey 2019; Watson and Nations 2019). Such perceptions may ultimately result in people resisting novel technologies such as SHAs or discontinuing their use (Ling et al. 2018; Raff et al. 2020; Raff & Wentzel 2018; van Offenbeek et al. 2013). However, although smart technologies, and SHAs specifically, have garnered significant scholarly interest, there appears to be limited research on the subject of technology resistance.

In this paper, we address this gap. Given the exploratory nature of our research endeavor, we pursue a developmental mixed-methods approach with two sequential studies, both qualitative and quantitative in nature, that build on each other (Venkatesh et al. 2013). Study 1 seeks to inductively explore the mechanisms underlying the resistance to SHAs. It utilizes mental models to thoroughly extract the cognitive structures and factors from individuals who have made a conscious choice not to adopt an SHA. Given that SHAs possess unique characteristics that radically differentiate them from technologies typically studied in the IS field (see Moussawi et al. 2022), we also expect to discover novel and technology-specific factors that drive consumer resistance (Cenfetelli 2004). Study 1 is guided by the following research question: What are the constructed ideas and beliefs that drive the resistance to SHAs? The second study builds on the results from study 1. We delve deeper into understanding one specific new inhibitor which we have identified, namely "perceived intrusion". Moreover, we draw on MacKenzie et al. (2011) and present the first steps toward developing a measurement instrument. Thus, the goal of the second study is to gain a conceptual understanding of perceived intrusion as a potential new driver of SHA resistance and based on this develop a standardized measurement instrument. The following research question guides our second study: What might a standardized instrument for measuring perceived intrusion from SHAs look like?

The remainder of the paper is organized as follows: The subsequent section will give an overview of the underlying theory. Next, the two studies and their preliminary results will be outlined. The paper concludes with our key contributions, derived implications, and an outlook of our future research.

2 Inhibitors in the Context of Technology Resistance

Most technology acceptance and adoption studies assume that people are generally receptive to new technologies or have first-hand experience with them (e.g., Moriuchi 2019). This pro-innovation bias, however, tends to obscure the fact that there are significant failure rates when it comes to high-tech innovation (Castellion & Markham 2013; Talke & Heidenreich 2014). In this context, consumer-side resistance and rejectionist attitudes represent a major driver for such failure (Talke & Heidenreich 2014). In contrast to acceptance, which represents factual behavior, resistance can be understood as a cognitive force that prevents such behavior (Bhattacharjee & Hikmet 2007; Kim & Kankanhalli 2009; Lewin 1947). This research focuses on active resistance which describes "an attitudinal outcome that follows an unfavorable evaluation of a new product" (Talke & Heidenreich 2014, p. 898). Importantly, active resistance must be distinguished from passive resistance, which describes a form of resistance triggered by adopter- and situation-specific factors such as an inclination to resist change and/or status-quo satisfaction (Ram & Sheth 1989; Talke & Heidenreich 2014; van Offenbeek et al. 2013). Most studies from the IS field examining resistance have focused on organizational contexts where resistance may emerge in response to the mandatory introduction of organizational technologies (e.g., Bhattacharjee & Hikmet 2007; Lapointe & Rivard 2005). In the context of this research, however, resistance may emerge in response to an innovative consumer technology where individuals are completely free to decide

whether they want to adopt it or not. In this case, active resistance is caused by negative object-based beliefs (i.e., inhibitors) that stem from the assessment of innovation characteristics and represents a deliberate and conscious form of resistance (Cenfetelli & Schwarz 2011; Ram & Sheth 1989; Talke & Heidenreich 2014). Hence, this research focuses on so-called resisting non-users (van Offenbeek et al. 2013). To understand active resistance, one must not only account for specific inhibitors but must also consider how these inhibitors interact with enabling factors (i.e., enablers) that are usually present even in the case of resistance (Cenfetelli 2004; Cenfetelli & Schwarz 2011). Drawing on Lewin's (1947) model of opposing forces, Cenfetelli (2004) advanced a dual-factor model of IT usage that focuses on the interplay of inhibitors and enablers and builds on three main assumptions: (1) some perceptions solely discourage technology usage, drive resistance (inhibitors) and are qualitatively different from the opposite of those that drive usage intentions (enablers); (2) inhibitors and enablers are independent and can co-exist; and, most importantly, (3) inhibitors and enablers have different antecedents and consequences. Cenfetelli's model argues that inhibitors take on a predominant role in the adoption process as they have much greater explanatory power compared to enablers (Cenfetelli 2004). That is, similar to the notion that "bad is stronger than good" (Baumeister et al. 2001) or that "losses loom larger than gains" (Kahneman & Tversky 1979), inhibitors can potentially override enablers. For instance, while people may feel that a new technology is useful and/or easy to use, these perceptions may be overruled by more powerful inhibitors. Importantly, the model also suggests that inhibitors and resistance can impact adoption intentions directly, as well as indirectly through enablers. That is, apart from directly undermining adoption intentions, inhibitors may also indirectly decrease intentions by, for example, affecting how useful individuals consider a new technology to be in the first place (Cenfetelli 2004; Cenfetelli & Schwarz 2011). Past studies on technology resistance have focused on artifacts such as apps (Prakash & Dash 2022), healthcare or medical information technology (Bhattacharjee & Hikmet 2007; Lapointe & Rivard 2005), human resources information systems (Laumer et al. 2016), or online teaching platforms (Craig et al. 2019). Importantly, these studies show that technology resistance is highly context- and technology-dependent. That is, while a few inhibitors – such as perceived threat (e.g., Bhattacharjee & Hikmet 2007; Lapointe & Rivard 2005) or high cost combined with a rapid technological change (Venkatesh & Brown 2001) – may span multiple domains, many inhibitors are specific to a technological artifact (e.g., Bhattacharjee & Hikmet 2007; Cenfetelli & Schwarz 2011; Craig et al. 2019). Put differently, as technologies evolve, so may the inhibitors (Raff & Wentzel 2018).

Against this background, this study focuses on a relatively new technological artifact, namely SHAs, that may give rise to new inhibitors. Mental models, which are shaped by people's underlying beliefs and understandings of the world (Rouse & Morris 1986), can offer valuable insights into the inhibitors that may lead to resistance to SHAs. Therefore, in the next step, our research uses mental models to reveal the belief structures related to SHAs, specifically focusing on the enablers and inhibitors.

3 Study 1: An Exploration of Mental Models

3.1 Method, Procedure, and Analysis

To get a comprehensive picture of the underlying belief structures regarding SHAs, in study 1, we explore mental models by using a mix of a (1) projective technique (collage construction) and subsequent qualitative (2) in-depth interviews. This represents an established approach to studying mental models (Zaltman & Coulter 1995). Moreover, the overall taken mental model approach has found its application in previous IS studies (e.g., Chiu and Staples 2012) and was considered to be suited best to study the multifaceted and controversial understandings of the IT-artefact under scrutiny. Compared to standard verbal research methods, using projective techniques allows people to express themselves more directly, thoroughly, and accurately (Levy 1985).

During the subsequent qualitative interviews, the participants could explain their collage and the key narrative underlying each picture. The method used to recruit interview participants was a purposeful sampling technique based on a small non-probability sample. This is an adequate approach when

searching for participants “who have experienced the central phenomenon or the key concept being explored” (i.e., resistance) (Creswell and Piano Clark 2018, p. 173). As the aim of Study 1 was not to generalize from our data but to generate initial insights that form the basis of Study 2, a sample size of around ten participants can be considered adequate (Creswell and Piano Clark 2018). Specifically, we recruited a range of non-adopters of SHAs and used filtering questions to identify 10 individuals among them who actively resisted the adoption of an SHA (age: M=31.7 years; gender: M=70% female). The study was conducted in German in a controlled laboratory setting. All participants took part voluntarily. In the (1) collage construction part, all participants had a laptop with an Internet connection and Microsoft PowerPoint available. This gave participants access to a large variety of image and text items as input materials. Participants then had as much time as they wanted to use these materials to arrange a collage representing their beliefs about SHAs. In the later (2) interview part, participants were asked to provide a thorough description of the selected pictures in their collages. This involved explaining the connections between the pictures, as well as the underlying narratives and rationales behind them. A laddering approach was applied to reveal the fundamental underlying beliefs of each picture. In our analysis interview transcripts and collages were examined. All interviews were digitally recorded and fully transcribed. Computer-assisted qualitative data analysis software (NVivo 11) was used for the subsequent open coding approach. Two coders independently coded inhibitors and enablers, yielding a substantial inter-rater agreement captured by a Cohen’s Kappa of 0.72. The final coding scheme consisted of 12 inhibitors and 11 enablers.

3.2 Preliminary Findings

Due to space limitations, the enablers will not be considered in more detail here and only the most important results regarding the discovered inhibitors will briefly be presented. A total of 10 collages and interviews have been analyzed (collage construction time: M=34.5 minutes, SD=15.6; interview length: M=34.1 minutes, SD=6.9). To illustrate the collages from the participants, two example collages can be found in Figure 1. A fine-grained set of 12 different inhibitors to the adoption of SHAs could be revealed. A full list of those inhibitors and a short description derived from the interview verbatim can be found in Table 1. Feeling scared emerged as the most significant inhibitor during the in-depth interviews (13.1%) and thus seems to be a major inhibiting force. More identified inhibitors are constant observance (12.1%), privacy concerns (11.1%), loss of control (10.1%), immaturity of technology (9.1%), other specific negative consequences (9.1%), concerns about artificial intelligence and autonomy (8.1%), existential insecurities (8.1%), lack of perceived benefits (7.1%), fear of manipulation (6.1%), fear of cyber-attacks (5.1%), and financial barriers (1%).

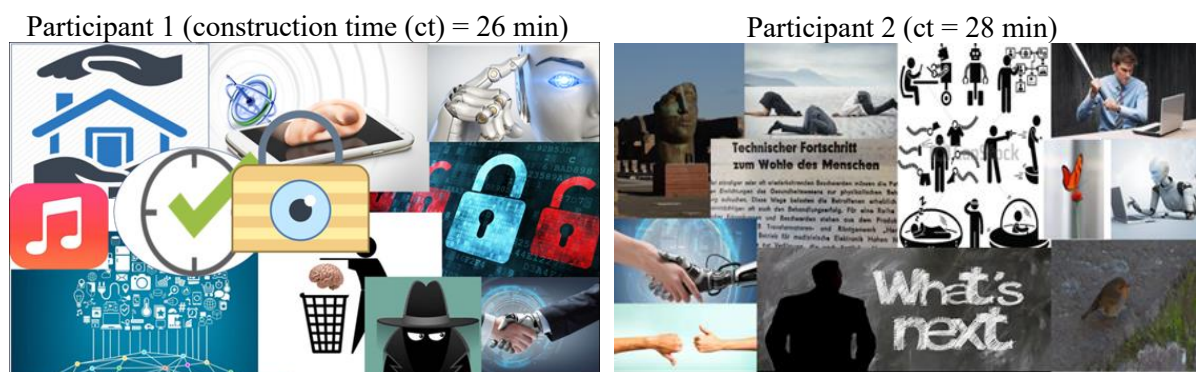


Figure 1. Example Collages of Two Participants

Inhibitor	Description
Feeling scared	A latent, unspecified feeling of scariness that is detached from any concrete fear.
Constant observance	Doubts of knowing when or if at all SHAs are actually turned off and at what time they are recording.
Privacy concerns	Concerns about whether uniquely identifiable data is collected, stored, and used.
Loss of control	A perceived loss of control of one’s home induced by SHA.
Immaturity of technology	The immaturity of technology leading malfunctions and frustration.
Other specific negative consequences	Negative experiences in day-to-day use such as being confused or overwhelmed.
Concerns about artificial intelligence and autonomy	Perceived product intelligence and product autonomy drive perceived risks and perceived complexity.
Existential insecurities	Existential insecurities concerning the self, e.g., the feeling of getting replaced by technology or an increased speed of life.
Lack of perceived benefits	SHAs are a gimmick and do not add real value to people’s daily lives.
Fear of manipulation	SHAs might not function in the interest of the user but in the interest of a corporation and thus might manipulate one via personalized pricing and advertising.
Fear of cyber-attacks	Fear of becoming vulnerable through cyber-attacks.
Financial barriers	SHAs are expensive and not affordable.

Table 1. Description of Identified Inhibitors to the Adoption of SHAs

4 Study 2: Development of a Measurement Construct

While many of the identified inhibitors have been extensively studied individually in research on (smart) technology acceptance and resistance (see, e.g., Mani & Chouk 2018, Benlian et al. 2020) from our perspective, a novel inhibitor has emerged in the context of SHAs. That is, the interviews revealed a significant interrelationship of the four identified inhibitors (1) feeling scared, (2) constant observance, (3) privacy concerns, and (4) loss of control (Participants often used the same collage images to refer to all four aspects, and in interviews, these were often mentioned together, with similar implications for resistance). As a result, we began considering the possibility that these traits jointly could form a new psychological construct that predicts resistance to smart technologies. We believed this idea merited further exploration and thus coined the term “perceived intrusion” to describe this construct. We assume that the perceived intrusion is composed of the following components: (1) the degree to which one feels scared which embodies a revealed latent, unspecified feeling of scariness that is detached from any

concrete fear. Interview participants associated the feeling with something like hosting an invisible guest in their homes. Further components are to perceive (4) a loss of control over the product's actions regarding the (3) accumulation and sharing of personal information and (2) perceived insecurities regarding their physical presence and perception of permanence, meaning the inability to definitively turn the smart device off or to be sure whether the smart device is switched on or off. Thus, perceived intrusion seems not only to be understood as a breach of privacy (as examined in studies like Benlian et al. 2020), but also as a physical form of intrusion by simply being present (e.g., only by the fact that it is located in the home) and concerns about whether the technology is turned on or off. Based on the results of our first study, in the following, we present the first steps in developing the specific construct of perceived intrusion, which is expected to be an important predictor of resistance to SHAs. The proposed scale development is based on steps proposed by MacKenzie et al. (2011). Thus, firstly, the construct is conceptually defined. Next, further interviews were pursued to get richer verbal data for item generation. Following this, an initial item pool for the previously described dimensions is generated. In multiple steps of revision, these items are condensed and refined. Lastly, the created item pool is used to conduct a pre-test in order to further refine the construct via exploratory factor analysis (EFA). Below, these steps will be outlined in more detail.

4.1 Conceptualization of the Construct

When developing a construct, a precise conceptualization is crucial to describe a phenomenon of theoretical interest as well as to be able to generate measurement items that fit the construct (MacKenzie et al. 2011). To further explore the nature of the focal construct and to enable the generalizability of our scale to other smart technologies we conducted 20 additional interviews on three different smart products from the smart home context in addition to the interviews from our initial study. The interviews were conducted in person and in a semi-structured manner. The interview participants were selected from different ages and professions to guarantee broad and diverse input (age: $M=37.5$ years; gender: $M=50$ % female). First, participants were given descriptions of smart products (e.g., smart toy, smart vacuum cleaner, smart headphone). Afterwards, they were prompted to share their overall thoughts as well as what makes them perceive these smart products as potentially scary or intrusive. Based on the interview transcripts, an expert workshop with five research assistants and one Ph.D. student was carried out to develop a concise definition for the concept of perceived intrusion. In this process, the initial four dimensions derived from study 1 were further refined and narrowed down to three final dimensions: privacy, loss of control, and permanence. In so doing, privacy referred to general privacy concerns, i.e., third parties obtaining personal data. Loss of control refers to the situation where a user of smart technology is unable to determine which personal information is being shared and with whom it is being shared. In other words, it describes a scenario where the user lacks control over the dissemination of their personal information through the smart technology. Lastly, permanence denotes the perceived insecurities regarding the perception of permanence, meaning the inability to be sure whether the smart device is switched on or not. Our final conceptualization reads as follows: "Perceived intrusion describes the degree to which a person perceives that a particular smart technology would lead to continuous observation and uncontrolled and undesired sharing of privacy". We treat our construct as a formative construct of the form: $\eta = \sum_{i=1}^{\eta} \gamma_i x_i + \zeta$ where γ_i is the coefficient capturing the effect of the indicators x_i on latent variable η and ζ is an error term (MacKenzie et al. 2011).

4.2 Item Generation, Pre-test, and Preliminary Findings from the EFA

Based on the definition and the three named dimensions, a set of candidate items was generated and polished in several rounds of refinement towards an initial item set. The item generation was based on a review of existing literature, the rich interview verbatim, and expert evaluations (Moore & Benbasat 1991). At the end of this process, 27 items were defined and were implemented in a survey for our scale pre-test. Of the 27 items 11 form the dimension "privacy", 8 form the dimension of "loss of control" and another 8 the dimension "permanence". In the next step, our initial item pool had to be pre-tested through a survey for further scale purification. To make the item statements easy to understand, we

choose Amazon Echo’s ALEXA as an illustrative product example in our items. We used a seven-point Likert scale ranging from (7) strongly disagree to (1) strongly agree to measure the answers of the participants. The final survey was launched on Amazon MTurk. After the data collection, we cleaned our data in terms of survey completion rate and completion time. As a result of this process, a total 276 participants remained for the exploratory data analysis (Age: M=29.5; gender: M=53% female). Since we want to explore our data and examine if our three conceptually defined dimensions hold in a quantitative empirical pre-test, we analyzed our data using an EFA. The EFA was pursued in SPSS Statistics. Due to constraints, only the most important results from the EFA can be presented in the following. First, we removed items that had factor loadings lower than 0.60. Additionally, we deleted items that did not display statistically significant correlations with the expected dimension but instead had stronger correlations with other dimensions. These item deletions resulted in eight out of the initial eleven items for the factor “privacy”. Within the factor “loss of control”, no item was deleted. On the contrary, the factor “permanence” was reduced to two items (see Table 2). In sum, the EFA lead us to the removal of 9 items from the initially defined 27 items. Overall, our three-factor solution accounted for approximately 80.83% of the total variance. Lastly, the reliability analysis via Cronbach’s Alpha (α) showed good values of ≥ 0.9 for each dimension respectively.

Item	Factor Loadings		
	Privacy $\alpha=0.97$	Loss of control $\alpha=0.93$	Permanence $\alpha=0.95$
I feel spied on by ALEXA	0.959		
ALEXA infiltrates my private life	0.906		
It bothers me that ALEXA is collecting personal information	0.959		
I feel like more private information than desired is collected through ALEXA	0.927		
ALEXA uses my personal data for unwanted purposes	0.705		
My private data is less protected against third parties when using ALEXA	0.663		
I feel like ALEXA is collecting information that is too personal	0.779		
ALEXA is intrusive	0.704		
I feel like ALEXA is always on			0.918
ALEXA is active at all time			0.930
I cannot control which private information ALEXA uses		0.829	
I am not able to control how much private data is collected by using ALEXA		0.803	
Using ALEXA, I feel like losing control about what kind of personal information is collected		0.666	
I am not able to stop ALEXA from collecting personal data		0.813	
I do not have control over ALEXA regarding the sharing of my private data with third parties		0.868	
ALEXA takes over decisions without the ability for me to intervene		0.807	

Item	Factor Loadings		
	I have the feeling that the connectivity of ALEXA with other products is not in my control		0.809
I cannot control ALEXA		0.857	

Table 2. Factor Loadings from Rotated Three-Factor PAF after Item Reduction (N=276)

5 Discussion, Contribution, and Outlook

The critical role of SHAs in the advent of smart homes, on the one hand, and the growing concerns about them, on the other, require deeper insights into the inhibitors that may be driving resistance. In this study, our initial focus was on identifying potential inhibitors through the process of mental model elicitation. Next, we presented the preliminary status of a scale development procedure for the novel identified construct “perceived intrusion”. The results of our EFA are in support of the three dimensions that we initially conceptualized for the construct. Our next steps in the scale development process will include pursuing a CFA to clarify the congeneric measurement properties of the construct, testing convergent, nomological, and discriminant validity, as well as testing its applicability across different smart product contexts (MacKenzie et al. 2011).

Overall, we believe that our research can stimulate the current scientific discourse in multiple ways. First, this work adds to research on the dark side of smart consumerized IT (e.g., Benlian et al. 2020) by proposing a new, previously undiscovered inhibitor. In this way, we are counteracting the trend in IS research to view new digital technologies primarily from the perspective of “technology as a solution” (Rowe 2018). Additionally, we believe that our research methodology aligns with Grover and Lyytinen’s (2015) request of pushing IS research to the edges. Specifically, our approach, demonstrated in study 1, contributes to the “left edge” by introducing a novel form of inductive knowledge creation that leads to an innovative dataset (collages). In addition, our research adds to practice. That is, the identified inhibitors may have implications for technology design. Since the inhibitors explain why people decide against SHAs, technology designers may use them as entry points to reduce resistance and promote the diffusion of SHAs. Lastly, it is important to interpret our findings in light of their limitations. Study 1, for example, was conducted with a relatively small sample size, raising questions about its representativeness for the larger population. Therefore, we encourage further quantitative research to confirm our exploratory findings. Additionally, since our exploratory data collection was limited to Germany, the cultural specificities of our findings may not be generalizable to other contexts.

In conclusion, we hope that future studies will pick up our novel construct and develop it further and/or apply it across different smart product contexts. Moreover, it would be worthwhile for future research to investigate how different design features of SHA devices affect the perceived level of intrusion. For example, software-side aspects such as algorithmic transparency versus non-transparency (Watson and Nations 2019), as well as hardware-related aspects like a stand-alone device versus one embedded in everyday objects, may have varying impacts on the perception of intrusion. This could also contribute to current research on design principles for smart technologies (see Touzani et al. 2018; Benlian et al. 2020; Moussawi et al. 2022; Tereschenko et al. 2022). Furthermore, in future research, there is potential to investigate other inhibitors that have been identified (such as feeling scared) and explore how they interact with enabling factors in dual-factor type resistance studies.

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