International Journal of Information Management 74 (2024) 102720

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Research article

Perceived creepiness in response to smart home assistants: A multi-method study

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A R T I C L E I N F O

Keywords:
Technology resistance
Perceived creepiness
Smart home technology
Smart home assistants
Smart product
Multi-method study

A B S T R A C T

Smart home assistants (SHAs) have gained a foothold in many households. Although SHAs have many beneficial capabilities, they also have characteristics that are colloquially described as creepy – a fact that may deter potential users from adopting and utilizing them. Previous research has examined SHAs neither from the perspective of resistance nor the perspective of creepiness. The present research addresses this gap and adopts a multi-method research design with four sequential studies. Study 1 serves as a pre-study and provides initial exploratory insights into the concept of creepiness in the context of SHAs. Study 2 focuses on developing a measurement instrument to assess perceived creepiness. Study 3 uses an online experiment to test the nomological validity of the construct of creepiness in a larger conceptual model. Study 4 further elucidates the underlying behavioral dynamics using focus group analysis. The findings contribute to the literature on the dark side of smart technology by analyzing the triggers and mechanisms underlying perceived creepiness as a novel inhibitor to SHAs. In addition, this study provides actionable design recommendations that allow practitioners to mitigate end users' potential perceptions of creepiness associated with SHAs and similar smart technologies.

1. Introduction

In recent years, smart home technologies have become widespread, contributing to the digitization of individuals (Benlian et al., 2019; Mamonov & Koufaris, 2020; Turel et al., 2020). These technologies usually consist of networks of interconnected smart devices that communicate with each other and are steered by a central control unit (Rijsdijk & Hultink, 2009; Raff et al., 2020). In specific, as integral parts of these smart home systems (Canziani & MacSween, 2021; Pal et al., 2021), smart home assistants[1] (hereinafter SHAs) serve as central control units for users to manage and monitor smart home appliances, such as lighting, heating, security systems, and entertainment devices. In this way, SHAs function as personal helpers for the home environment (Pfeuffer et al., 2019b). SHAs bring about a transformation to traditional buttons, replacing them with voice commands. They comprise a central command center in the form of voice software, such as the Alexa software, and a hardware device that operates under the control of this software, like the Amazon Echo speaker (Kim & Choudhury, 2021). This way, users can interact with their smart homes effortlessly and in a human-like manner using voice-based communication through virtual assistants like Alexa, Cortana, or Siri (Benlian et al., 2019; Kim & Choudhury, 2021; Mallat et al., 2017).

Despite the promising potential of SHAs, they are also frequently described as being *creepy*. For example, the Mozilla Foundation's popular buyer's guide, in which consumers are invited to rank smart products based on perceived concerns, lists SHAs among the products classified as highly creepy (Mozilla, 2023). In this regard, there have been numerous reports of SHAs engaging in actions that are perceived as

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[1] Within the existing literature, different terms have been used to refer to devices such as the Amazon Echo or Google Home. Notably, terms like Voice Activated Personal Assistants (VAPA) (Mallat et al., 2017), Voice-based Digital Assistants (VBDA) (Vimalkumar et al., 2021), intelligent personal assistant (IPA) (Hu et al., 2021), or Personal Intelligent Agents (PIA) (Moussawi et al., 2022) have been employed. It is important to note that these terms are interchangeable and share the idea of a software as a central command center (e.g., Alexa) and a hardware device controlled by the software (e.g., Amazon Echo speaker). To standardize the terminology in this study, we use the term "Smart Home Assistant" (SHA) as an umbrella term when referring to these devices.

https://doi.org/10.1016/j.ijinfomgt.2023.102720
Received 4 November 2022; Received in revised form 12 October 2023; Accepted 12 October 2023

"creepy" (Watson & Nations, 2019; Selligent, 2019). For instance, SHAs have shocked residents by emitting spooky witch-like laughter sounds in the middle of the night (Badkar, 2018) or by suddenly activating themselves and listing the names of nearby funeral homes (Segarra, 2018). In addition, there are reports where SHAs secretly recorded private conversations and sent them to random contacts from the device's contact list (Shaban, 2018).

While these anecdotal incidents are obviously the result of SHAs malfunctioning, some of the skills and characteristics that allow SHAs to provide unique benefits may also be inherently associated with perceptions of creepiness (Shank et al., 2019). For example, a new Alexa skill is planned to imitate the voices of dead relatives (Blanchet, 2022). Moreover, extant research found that technological artifacts that are increasingly human-like may appear spooky – a finding that has been revealed for robots in general (Mori et al., 2012) and voice technologies in particular (Yip et al., 2019). Furthermore, an SHA that is always listening and whose decision and recommendation logic is not completely transparent may feel more like a nightmare than a great vision (Langer & König, 2018; Lynskey, 2019; Watson & 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).

In light of perceptions of digital technologies as being creepy (Langer & König, 2018; Langer, König & Fitili, 2018; Ostrom et al., 2019), Watson and Nations (2019) have called for a more in-depth examination of their creepiness. However, existing studies that have investigated SHAs from a resistance perspective (e.g., Cao & Zhao, 2019; Lau et al., 2018; Pfeuffer et al., 2019a; Vimalkumar et al., 2021) speak neither to how perceptions of creepiness may affect people's responses to SHAs nor to how specific design factors of SHAs may trigger these perceptions.

In the present research, we address this gap and examine the concept of creepiness as a potential novel inhibitor to the adoption of SHAs. Our overarching research question is: *What are the mechanisms (i.e., triggers and effects) of perceptions of creepiness in response to smart home assistants?*

To answer this question, we aim to (a) develop a standardized instrument that measures perceptions of creepiness towards SHAs, (b) identify design-side factors that trigger perceptions of creepiness, and (c) elucidate the mechanisms of perceived creepiness in a larger conceptual model. To address these aims, we employ a multi-method research design (Maier et al., 2023; Venkatesh et al., 2013). This comprises four interrelated studies: a qualitative pre-study ($N = 10$), a scale development study to develop a measurement instrument for creepiness based on two independent data sets (main study $N = 326$ & cross-validation $N = 300$), a vignette-based experimental study ($N = 553$), and an additional focus group study ($N = 6$).

Our work makes several contributions. First, it sheds light on resistance to SHAs and, specifically, perceived creepiness as a novel inhibitor, offering a novel perspective on the negative facets of smart technology. By doing so, it fills a gap in the existing literature and offers valuable insights to the body of research focused on uncovering the negative aspects of smart technology (e.g., Brous et al., 2020; Cenfetelli, 2004; Ilie & Turel, 2020; Jain et al., 2023; Marikyan et al., 2019; Vimalkumar et al., 2021).

Second, this work contributes insights into the often-neglected duality of user-side considerations in adoption processes, examining not only the enabling beliefs but also the inhibiting ones, as well as their interrelationships, thus creating a more holistic picture of potential impeding mechanisms (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011).

Third, our findings extend the literature by studying the effects of different hardware- and software-side design characteristics in shaping perceived creepiness and resistance to SHAs. In this manner, this research responds to recent calls to investigate the adoption process of SHAs and other smart technology in the context of digitization at the individual level (e.g., Mallat et al., 2017; Turel et al., 2020; Yang et al., 2021), while simultaneously also taking into account specific design features (Baiyere et al., 2020; Schuetz & Venkatesh, 2020).

Last, by examining the concept of creepiness in the domain of SHAs, the present research contributes to the emerging body of literature on creepiness in technology contexts (Langer & König, 2018; Sullivan et al., 2020; Tene & Polonetsky, 2014; Yip et al., 2019). Our research addresses previous calls to enhance the understanding of the structural characteristics of the phenomenon of creepiness (Watson & Nations, 2019) and proposes a scale to measure perceived creepiness as an inhibitor to SHAs.

The remainder of this paper unfolds as follows. Sections 2 and 3 introduce the theoretical background and hypotheses. Section 4 details our three complementary studies, including their respective empirical results. Finally, Sections 5 and 6 conclude the paper with a discussion of the main findings, implications, and avenues for future research.

2. Theoretical background

2.1. Research on smart home technology adoption

Smart home technologies have rapidly gained popularity and become an integral part of consumers' daily lives, showing the fastest growth rate in the consumer technology market (Malodia et al., 2021). Playing a critical role in smart home environments (Canziani & MacSween, 2021; Pal et al., 2021; Pfeuffer et al., 2019b), SHAs are leading the way in this advancement (Malodia et al., 2021). As the use of SHAs has expanded, scholars have stepped up efforts to understand them (Marikyan et al., 2019). So far, these efforts have mainly focused on examining their benefits as well as the technical intricacies of these devices (Marikyan et al., 2021). However, Marikyan et al. (2019) note that there is still a dearth of research on the consumer perspective, especially concerning acceptance and resistance.

Among the existing studies on smart home technologies that investigate acceptance and its respective drivers, Shin et al. (2018), for example, find that compatibility, perceived ease of use, and perceived usefulness positively influence the intention to purchase smart home technologies. Marikyan et al. (2021) largely confirm these results, showing that the adoption of smart home technology is driven by the perception of whether using it is effortless; additionally, if it is perceived as being easy to use, the technology will also be perceived as being more useful. Along similar lines, Canziani and MacSween (2021) and Moussawi et al. (2022) show that the perceived utility/usefulness of SHAs positively affects the intention to use them. Further studies show that besides perceived usefulness, SHA acceptance is also driven by factors such as perceived social presence, trust, and rapport (Fernandes & Oliveira, 2021), as well as competence and warmth perceptions (Hu et al., 2021).

The scant existing research on *resistance* to smart home technologies and SHAs highlights distinct barriers that hinder their widespread adoption. These barriers can largely be categorized into four main groups. The first category refers to the costs of smart home technologies, that is, acquisition costs (Balta-Ozkan et al., 2013) or maintenance costs (Ehrenhard et al., 2014). The second category comprises barriers related to utilitarian aspects, such as perceived complexity (Chouk & Mani, 2019), perceived performance risk (Wilson et al., 2017), and perceived lack of utility (Lau et al., 2018). The third category captures concerns about consumer privacy and security, namely security risk (Balta-Ozkan et al., 2013; Chouk & Mani, 2019; Wilson et al., 2017), privacy risk related to SHAs (Hong et al., 2020; Lau et al., 2018; Mani & Chouk, 2017), fear of government surveillance (Chouk & Mani, 2019), and lack of trust in SHA manufacturers (Lau et al., 2018). Finally, the fourth category consists of psychological barriers, such as ceding autonomy (Wilson et al., 2017), loss of control (Balta-Ozkan et al., 2013), disturbance of peace of mind (Hong et al., 2020), and strain and interpersonal conflicts induced by SHAs (Benlian et al., 2019).

While the findings outlined above contribute to our understanding of drivers and barriers to smart home technologies and SHAs in specific, they do not address the aspect of creepiness. In this respect, Marikyan et al. (2019) underscore the need to delve deeper into emotional and psychological factors that could influence consumer adoption or rejection of smart home technologies, with particular attention to the cognitive processes along adoption stages, including pre-adoption. However, before delving deeper into the concept of creepiness, it is necessary to thoroughly explore the phenomenon of technology resistance and the role of inhibitors.

2.2. Technology resistance and the role of inhibitors

Most technology acceptance and adoption studies assume that people are generally receptive to new technologies or have first-hand experience with them (e.g., Koufaris, 2002; Moriuchi, 2019). This pro-innovation bias, however, tends to overshadow the reality of substantial high-tech innovation failures (Castellion & Markham, 2013; Sheth & Stellner, 1979; Talke & Heidenreich, 2014). Consumer resistance and rejectionist attitudes are major drivers of such failures (Talke & Heidenreich, 2014).

In contrast to acceptance, which represents factual behavior, *resistance* can be understood as a cognitive force that precludes such behavior (Bhattacherjee & Hikmet, 2007; Kim, & Kankanhalli, 2009; Lewin, 1947). The present research focuses on *active resistance*, "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*, a form of resistance triggered by adopter- and situation-specific factors such as an inclination to resist change and/or satisfaction with the status quo (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., Bhattacherjee & Hikmet, 2007; Lapointe, & Rivard, 2005; Markus, 1983). The present work diverges from prior research by examining resistance as a response to emerging technologies in the consumer domain, where individuals freely exercise agency over their adoption decisions. In this setting, active resistance arises from negative object-based beliefs (i.e., *inhibitors*), which emerge from the evaluation of innovation characteristics and manifest as a deliberate and conscious form of resistance (Cenfetelli & Schwarz, 2011; Ram & Sheth, 1989; Talke & Heidenreich, 2014). Hence, our 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 driving 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 and 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.

Centefelli's model argues that inhibitors take on a predominant role in the adoption process as they have much greater explanatory power than enablers do (Cenfetelli, 2004). As "bad is stronger than good" (Baumeister et al., 2001) and "losses loom larger than gains" (Kahneman & Tversky, 1979), inhibitors can override enablers. Importantly, Centefelli's model also suggests that inhibitors and resistance may affect adoption intentions directly as well as indirectly through mediating enablers. That is, apart from directly undermining adoption intentions, inhibitors may also indirectly decrease adoption intentions, for example by downgrading 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), mobile wallets (Leong et al., 2020), healthcare information technology (Bhattacherjee & Hikmet, 2007; Lapointe & Rivard, 2005), human resources information systems (Laumer et al., 2016), and online teaching platforms (Craig et al., 2019). These studies show that technology resistance is highly context- and technology-dependent. That is, while a few inhibitors – such as perceived threat (e.g., Bhattacherjee & Hikmet, 2007; Lapointe, & Rivard, 2005), privacy-related concerns (e.g., Hsu & Lin, 2018) and high cost combined with rapid technological change (Venkatesh & Brown, 2001) – may span multiple domains, many inhibitors are specific to a particular technological artifact (e.g., Bhattacherjee & Hikmet, 2007; Cenfetelli & Schwarz, 2011; Craig et al., 2019; Mahmud et al., 2017). Thus, as technologies evolve, so do the inhibitors (Raff & Wentzel, 2018). Against this background, the present research focuses on an innovative technological artifact, the SHA, which yields not only radically new capabilities but may also give rise to new inhibitors, such as perceived creepiness.

2.3. Perceived creepiness as an inhibitor to SHA adoption

In social contexts, McAndrew and Koehnke (2016) define perceived creepiness as "anxiety aroused by the ambiguity of whether there is something to fear or not and/or by the ambiguity of the precise nature of the threat that might be present" (p. 10). A common trigger of creepiness in social contexts is the masked, disguised, or opaque nature of another person (McAndrew & Koehnke, 2016; Park, 2018; Watt et al., 2017). In such cases, it is difficult to grasp that person's state of mind and intentions and this feeling of the unknown causes perceptions of creepiness (Phillips, 2020; Watt et al., 2017). The state of being masked may be figurative – in the sense of the feeling that a person is hiding their true emotions – or literal. Because clowns often hide their true emotions behind makeup or masks, they are often perceived as creepy rather than funny (Clasen et al., 2020; McAndrew, 2017). Masks are also often used in horror films and theater plays to hide the performers' faces – and thoughts and feelings – and to instill a creepy mood in the audience (Heller-Nicholas, 2019; Honigmann, 1977; Nummenmaa, 2021).

In the present research, we argue that perceptions of creepiness, akin to related psychological responses like fear or anxiety (e.g., Brown et al., 2004; Thatcher et al., 2007) or human personality traits like perceived intelligence (e.g., Moussawi et al., 2022), can extend beyond social interactions involving humans and also arise in response to technologies, such as SHAs. Moreover, and similar to social contexts, we expect that the opaque interfaces of SHAs can function like a mask, hiding their decision-making processes and their algorithms, and will, thus, play a decisive role in triggering perceptions of creepiness.

In addition, we argue that these perceptions of creepiness are distinct from potentially related concepts describing psychological reactions to technology such as the uncanny valley effect, fear, or anxiety. Research on the uncanny valley argues that technology that imperfectly resembles human beings can easily seem eerie (Mathur & Reichling, 2016; Mori et al., 2012). Whereas anthropomorphic design features may elicit eerie feelings because they raise expectations of a human likeness which remain unfulfilled in subsequent interactions (Pfeuffer et al., 2019b), feelings of creepiness may be triggered by ambiguity associated with the non-transparent nature of SHAs regarding their decision-making processes and underlying algorithms. In a similar vein, creepiness is also distinct from constructs such as fear and anxiety. While those constructs are often used more or less interchangeably (Sylvers et al., 2011), fear can be conceptualized as strong arousal induced by an acute and concrete threat culminating in coping behaviors such as fight or flight responses (Epstein, 1972; Langer & König, 2018), while anxiety is more future-focused and is a more diffuse arousal state that can typically be traced to a specific source such as an unresolved threat (Epstein, 1972). In the IS domain, anxiety has often been discussed as a form of apprehension that may result from the actual or anticipated use of IT systems (e.g., Brown et al., 2004). In this study, we understand a feeling of creepiness, as explained by McAndrew and Koehnke (2016) in relation to social contexts, as a form of subtle unease, an intuitive or instinctive feeling, triggered by a lack of transparency about whether there is a reason to feel threatened or frightened.

Given that SHAs can be conceptualized as cyber-physical bundles, encompassing a material layer with hardware properties and a virtual layer consisting of a software operating system (see also Balakrishnan & Dwivedi, 2021; Kim & Choudhury, 2021; Knote et al., 2021; Mishra et al., 2022; Raff et al., 2020), we propose that perceptions of creepiness can arise from either of these layers.

In what follows, we derive a conceptual model that postulates the specific effects and interplays of perceived creepiness, its potential software- and hardware-side triggers as well as effects on resistance, enablers, and usage intention.

3. Conceptual model and hypotheses development

3.1. Lack of transparency as a software-side trigger of perceived creepiness

On the software side, previous studies of digital technologies have highlighted the significant impact that algorithmic transparency, i.e., the way algorithms are employed, their inner workings (e.g., data lineage), and the outcomes they produce (e.g., recommendations), can have on users' perceptions (Bauer & Gill, 2023; Recker et al., 2021; Watson & Nations, 2019). While enhanced transparency mitigates negative perceptions, a dearth of transparency tends to foster feelings of strain, skepticism, and discomfort (Benlian et al., 2019; Watson & Nations, 2019). Furthermore, this can undermine confidence in the outcomes of digital technologies, such as recommendations or suggestions, and lead to creepy ambiguity or moments of "creepy surprise" (Langer & König, 2018; Recker et al., 2021; Shank et al., 2019; Tene & Polonetsky, 2014). Examples of such surprises are receiving People You May Know suggestions on Facebook or Instagram after having met someone in person or receiving ads from Instagram based on the use of the microphone of one's smartphone (Franklin, 2018; Watson & Nations, 2019). In particular, Watson and Nations (2019), as well as Torkamaan et al. (2019), emphasize the impact of the lack of transparency in recommendation algorithms and the data points they utilize, along with the eventual recommendations and decisions made by certain technologies, in potentially eliciting perceptions of creepiness.

In sum, we postulate that SHAs that employ software-side decision and recommendation algorithms that are low (high) in transparency should lead to higher (lower) levels of perceived creepiness. We posit:

H1. : *There is a negative relationship between the transparency in SHAs' decision and recommendation algorithms and perceived creepiness.*

3.2. Lack of tangibility as a hardware-side trigger of perceived creepiness

On the hardware side, feelings of creepiness may be triggered by a lack of physical tangibility. Following recent design trends in ambient and ubiquitous computing, smart home technologies are becoming increasingly intertwined with our environment (Bradshaw, 2020; Carsen, 2020). For instance, SHAs may be integrated into walls and ceilings (see the Klipsch Amazon Echo multi-room smart speaker system with in-ceiling or in-wall mount) or objects such as mirrors (see the smart mirror by ICON.AI), lamps, ovens, or speakers (Alang, 2019). Thus, SHAs are becoming more and more disembodied and starting to vanish as visible, tangible devices (Milne, 2019; Nuttall, 2019).

From the perspective of potential users, these developments may not be uniformly positive. In particular, previous service and innovation research has discussed the idea that the absence of tangibility may have a negative impact on perceptions of a company's offerings. For example, consumers may feel that purchasing services is riskier and more uncertain than purchasing products because services lack a spatial presence; thus, they are dematerialized, lacking a physical, tangible form that can be evaluated before purchase (e.g., Bardhi & Eckhardt, 2017; Laroche et al., 2004; Murray & Schlacter, 1990). Such feelings of risk and uncertainty increase in importance when consumers are psychologically close to services, as is the case with SHAs, where services are provided in the most intimate part of our lives, that is, our homes (Heller et al., 2021). Research on smart products – that is, products that have both physical and digital components – finds that relationships between firms and customers are frequently formed based on a physical device (e.g., an iPhone) (Raff et al., 2020). As consumers may find it easier to emotionally connect to tangible products than abstract services, a physical product may serve as a gateway for the creation of long-term relationships (e.g., Atasoy & Morewedge, 2018; Hoffman & Novak, 2018; Nägele et al., 2020; Raff et al., 2020). Thus, if such a tangible component is missing, users may be more distrustful and suspicious of a device.

In sum, this suggests that the hardware-side tangibility of an SHA as a physical device may be related to perceptions of creepiness. That is, SHAs that are low (high) in tangibility should lead to higher (lower) levels of perceived creepiness. We posit:

H2. : *There is a negative relationship between the tangibility of SHAs and perceived creepiness.*

3.3. The effect of perceived creepiness on resistance

Next, we will discuss how perceptions of creepiness may shape resistance to SHAs. We argue that perceptions of creepiness may cause people to resist adopting SHAs by evoking inhibiting object-based beliefs (Cenfetelli & Schwarz, 2011). In the context of social interactions, McAndrew and Koehnke (2016) assert the existence of inherent mechanisms within individuals that serve as creepiness detectors, enabling them to maintain a safe distance from individuals exhibiting eerie or suspicious traits. Building upon this notion, we propose that such creepiness detectors may also be at work when people are confronted with technological advancements, leading them to exhibit caution and maintain their distance from these devices. That is, people may refuse to use SHAs because of the creepy feelings triggered by them. We posit:

H3. : *Perceived creepiness has a positive relationship with resistance to SHAs.*

3.4. The consequences and biasing effects of resistance

The next part of our conceptual model focuses on how resistance affects enabling factors as well as usage intentions. As mentioned earlier, the dual-factor model of IT usage argues that inhibiting beliefs and resistance should never be examined in isolation but also in light of possible enablers. Hence, inhibitors and resistance may not only undermine adoption intentions directly but may also exert an indirect effect on intentions through distorting enablers (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011).

Regarding a direct effect, such a negative relationship between resistance and acceptance or usage intention has been demonstrated in previous research and across different technology contexts (e.g., Bhattacherjee & Hikmet, 2007; Guo et al., 2013; Prakash & Das, 2022). We posit:

H4. : *Resistance has a negative relationship with the intention to use SHAs.*

Moreover, beliefs that lead end users to resist adopting technology products and services may decrease their intention to use those products and services not only directly but also indirectly, through negatively influencing or biasing enablers like perceived usefulness and perceived ease of use (Cenfetelli, 2004). In this regard, Bhattacherjee and Hikmet (2008) propose two explanations for the biasing effect on enablers. Firstly, according to norm theory, negative perceptions receive more cognitive attention, are remembered better, and trigger greater information processing than positive ones (see also Kahneman & Miller, 1986). In addition, prospect theory posits that negative perceptions trigger a broader spectrum of emotional reactions than positive perceptions do (Baumeister et al., 2001; Kahneman & Tversky, 1979). Secondly, the presence of inhibitors tends to anchor one's overall perception of the target object, subsequently biasing all other perceptions, including those of enablers (Bhattacherjee & Hikmet, 2007).

Evidence supporting this biasing effect is reinforced by various studies across different technological contexts (Bhattacherjee & Hikmet, 2007, 2008; Guo et al., 2013; Nov & Schecter, 2012; Tsai et al., 2019). For example, previous research has consistently demonstrated that inhibitors and resistance beliefs exert a detrimental bias on the perceived usefulness of technologies, as exemplified in the context of healthcare information technology (Bhattacherjee & Hikmet, 2007, 2008), location-based services (Zhou, 2013), and social media (Sullivan & Koh, 2019). Drawing from these conceptual explanations and empirical findings, we posit:

H5. : *Resistance has a negative relationship with perceived usefulness.*

Moreover, inhibitors and resistance beliefs may taint individuals' perceptions of a technology's ease of use. This has been consistently demonstrated in various technology settings, as exemplified by Bhattacherjee and Hikmet (2008) and Nov and Schecter (2012) in healthcare information technology, telehealth services (Tsai et al., 2019), and by Guo et al. (2013) in the context of preventive mobile health services. Drawing from these insights, we posit:

H6. : *Resistance has a negative relationship with perceived ease of use.*

Finally, in the realm of technology acceptance research, the important role of perceived usefulness and perceived ease of use in driving intentions to use has long been well-established (Davis, 1989). Besides, studies in the more specific domain of technology resistance research have also consistently pointed to the significant positive influence of perceived usefulness and perceived ease of use on intention to use (e.g., Bhattacherjee & Hikmet, 2007; Guo et al., 2013; Lee, 2013; Tsai et al., 2019).

Regarding perceived usefulness, previous research on technology resistance has consistently shown its positive impact on usage intentions towards innovative technologies. For example, Bhattacherjee and Hikmet (2007) highlight its importance in the context of driving healthcare information technology adoption. Similarly, Tsai et al. (2019) and Sullivan and Koh (2019) confirm this relationship for telehealth services and social media, respectively. In sum, it can be postulated that perceived usefulness will also be positively related to the intention to use SHAs. We posit:

H7. : *Perceived usefulness has a positive relationship with intention to use SHAs.*

Along these lines, the enabling effects of perceived ease of use have previously been demonstrated in resistance studies across diverse technology contexts. For example, Lee (2013) finds that perceived ease of use is a significant enabler of the intention to use mobile e-books. Similarly, Guo et al. (2013) show that perceived ease of use is an important driver of the intention to use preventive mobile health services. Thus, it can be postulated that perceived ease of use will be positively related to the intention to use SHAs. We posit:

H8. : *Perceived ease of use has a positive relationship with intention to use SHAs.*

Fig. 1 summarizes the derived conceptual model of this study, which will be tested in our subsequent studies.

4. Methodology

To test our conceptual model and provide a comprehensive understanding of the association between consumer responses to SHAs and perceptions of creepiness, we employed a multi-method approach and conducted a total of four interrelated studies (Maier et al., 2023; Venkatesh et al., 2013).

First, a qualitative pre-study (Study 1) served as an initial exploration of the prevailing beliefs held by individuals who actively resisted the adoption of SHAs. By using mental models, the pre-study aimed to uncover the underlying thoughts, beliefs, and concerns associated with the resistance to adopting SHAs. Moreover, the pre-study sought to establish an initial understanding of whether perceived creepiness is indeed a factor that is relevant in the context of SHA resistance. The findings directly informed the design of the subsequent studies. As mentioned earlier, a reliable measurement instrument for perceived creepiness in the context of SHAs has not been developed. To address this need, we undertook Study 2, in which our primary objective was to create and validate a measurement instrument designed to capture the perceived creepiness concerning SHAs. In Study 3, we applied a vignette-based online experiment, specifically aimed at testing the nomological validity of our novel creepiness measurement and the relationships proposed in our conceptual model. This study allowed us to accurately evaluate perceived creepiness and its triggers and downstream effects. To gain deeper insights into the underlying behavioral dynamics and enhance our initial understanding, we conducted an additional focus group study (Study 4).

4.1. Study 1: exploration of mental models

To initially explore our idea that SHAs are associated with perceptions of creepiness, we conducted an inductive, qualitative pre-study. To this end, we explored the mental models of individuals who deliberately decided against the adoption of SHAs ($N = 10$, age: $M = 31.7$ years; gender: 70% female). Mental models are constructed, small-scale models of external reality that guide reasoning and decision-making (Carley & Palmquist, 1992; Rouse & Morris, 1986). They are commonly used to study perceptions of IT artifacts (e.g., Mettler & Wulf, 2019; Wells et al., 2017). For this purpose, we first employed a

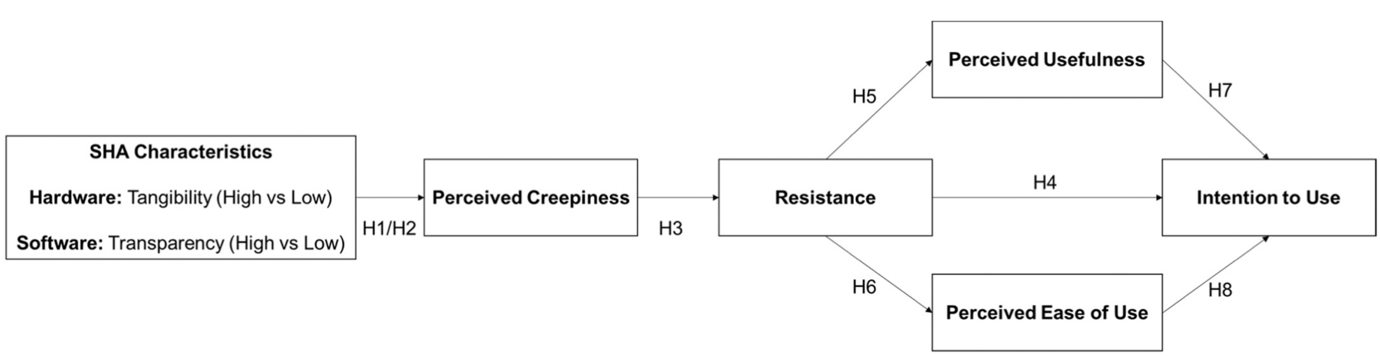

Fig. 1. Conceptual Model.

projective technique, asking our participants to construct collages, then continued with qualitative in-depth interviews (Zaltman & Coulter, 1995). The pre-study was conducted in a controlled laboratory setting and all participants took part voluntarily. To identify non-adopters who actively resisted SHAs, we used several filter questions such as "Have you ever thought about buying or using an SHA?" or "Would you find SHAs useful or see added value in such devices?" The people who indicated that they had thought about buying or using an SHA, but for some reason had decided against doing so, were classified as active resistors.

For the collage construction, participants were provided with an internet-connected computer with Microsoft PowerPoint installed. This gave participants access to a large variety of images as input materials. The instructions were kept to a minimum to obtain a comprehensive overview of participants' mental models and to remove any kind of bias (see Appendix 1 for more details). In the interviews following the collage exercise, participants were first asked some general questions about their thoughts regarding SHAs. Next, they were asked to describe their collages in detail, including a description of the links between the pictures as well as the narratives and rationales underlying each picture. To capture the deeper meaning of the pictures and to categorize them as inhibitors or enablers, the interviewer asked three questions about each picture (Appendix 1). Also, we used a laddering approach, following a pre-defined questionnaire, to reveal the origins and underlying meanings of each picture (Grunert & Grunert, 1995). In a final step, participants were given the opportunity to re-arrange their collages, create meaningful clusters of pictures, and draw links between them.

4.1.1. Data coding and analysis

In total, ten collages and interviews were analyzed (collage construction time: M = 34.5 min; SD = 15.6; interview length: M = 34.1 min; SD = 6.9). Fig. 2 shows example collages of two participants. Both the interview transcripts and collages were assessed in the analysis. All interviews were recorded digitally and fully transcribed. As proposed by Creswell and Piano Clark (2018), computer-assisted qualitative data analysis software (NVivo 11) was used for content analysis. To derive the consensus mental model, we followed the established guidelines of Zaltman and Coulter (1995), adhering to two main stages of analysis: (1) identification of key themes and (2) construction of the consensus mental model (a detailed description of these two stages and the respective analysis steps can be found in Appendix 2). In a last step, we used a centrality measure (C) to reveal how central the constructs were to the mental model (Yan & Ding, 2009). C reflects the ratio between the sum of text codes of a construct and the total number of text codes in the consensus mental model. Fig. 3 displays the final consensus mental model.

Fig. 2. Mental Model Collages of Two Participants.

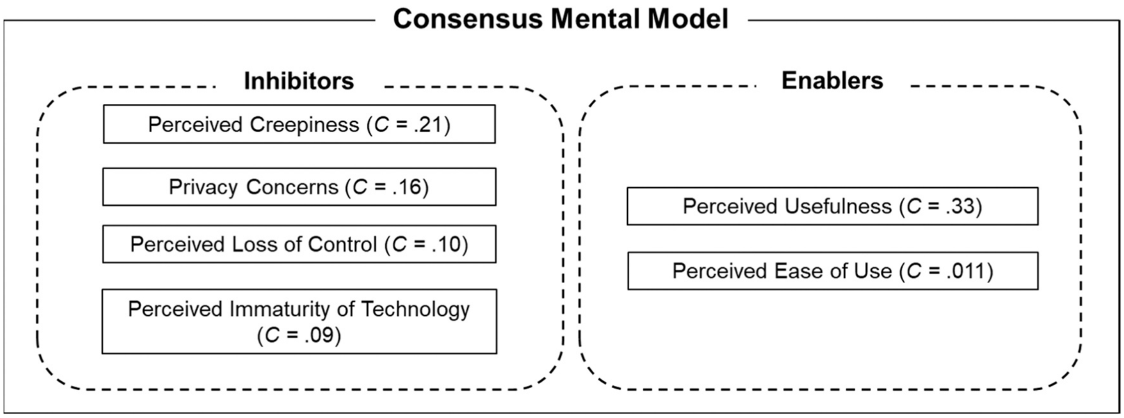

Fig. 3. Consensus Mental Model.

4.1.2. Findings

The final consensus mental model consisted of six constructs: four inhibitors and two enablers. As displayed in Fig. 3, participants' responses to SHAs were shaped by the interplay of the enablers perceived usefulness and perceived ease of use and the inhibitors perceived creepiness, privacy concerns, perceived loss of control, and perceived immaturity of technology. While most of these constructs have been extensively studied in research on technology acceptance and resistance, perceived creepiness emerged as a novel inhibitor for the context of SHAs (see e.g., Chouk and Mani, 2019, Mani and Chouk, 2019, Lee, 2020, or Pal et al., 2021 who examine the inhibiting role of constructs analogous to privacy concerns, loss of control, and perceived immaturity of technology in the context of smart technology). Moreover, the centrality measures indicate that *perceived creepiness* has the highest centrality of all the identified inhibitors. Thus, these findings offer initial evidence and a glimpse into the possibility that individuals who decide not to utilize SHAs may be influenced by a certain sense of creepiness with them.

4.2. Study 2: development of a measurement instrument for perceived creepiness

There is no established measurement instrument for perceived creepiness that specifically accounts for the context of SHAs. Hence, to provide robust evidence for the postulated relationships of our conceptual model, we had to develop a reliable measurement instrument. In this process, we based our steps on other studies from the IS field in which measurement scales have been developed (e.g., MacKenzie et al., 2011; Ormond et al., 2019; Polites et al., 2012; Tarafdar et al., 2020).

4.2.1. Scale development procedure

4.2.1.1. Item selection. In a first step, we generated an initial pool of items designed to match and represent the conceptual domain of the construct. This process was based on the findings of our pre-study and the extant literature on creepiness from the fields of IS, psychology, and HCI. Two other members of the university department – one professor and one post-doctoral researcher – were involved in the development of the initial item pool by making suggestions and discussing the face validity of these initial items. Since the construct of perceived creepiness is conceptualized as a unidimensional construct, we aimed for no further assignment of items into different sub-dimensions. This procedure ultimately left a broad initial pool of 31 items (see Appendix 3).

4.2.1.2. Scale purification. Next, we collected data through a survey study to purify the scale using exploratory and confirmatory factor analyses (EFA/CFA). We recruited $N = 313$ non-owners of SHAs from the United Kingdom, United States, Ireland, Australia, and New Zealand (*age range* = [18,69], $M_{age} = 32.24$, $SD = 11.96$, 60.6% female) who participated in return for financial compensation through the online platform Prolific (a platform known to deliver high-quality samples; see Peer et al., 2017). The sample size corresponds to the recommended number of respondents for factor analysis (see MacKenzie et al., 2011).

The survey was structured as follows. After reading an introduction to the study, participants learned about a fictitious SHA called QUANTUM that was characterized as having low tangibility and low transparency (see Appendix 4 for the stimulus material). Based on our conceptual model, we expected this configuration to trigger the highest perceptions of creepiness. Regarding tangibility, QUANTUM was described as being fully integrated into the walls and ceilings of one's home, vanishing as a physical device. Regarding transparency, the stimulus material relayed a fictitious conversation between QUANTUM and the alleged owner. In this conversation, the SHA gives its owner, Bobby, a recommendation for his next holiday destination: Tenerife. When Bobby asks how QUANTUM came to this suggestion, the device gives a highly opaque and vague answer. After being presented with this scenario, participants were asked to complete a survey that contained the items of the creepiness construct and a range of other measures (see next section).

4.2.1.3. Measures. To test for discriminant validity, we also assessed constructs that may potentially overlap with creepiness, namely privacy invasion (Ayyagari et al., 2011), uncertainty regarding the technology (Johnson et al., 2008), fear (Loyd & Gressard, 1984), privacy concerns (Lwin et al., 2007) and trust in the technology (Thomson, 2006). An overview of all items used in Studies 2 and 3 is provided in Appendix 5. In the study, all items were fully randomized.

We measured perceived creepiness using the 31 items from the initial pool (see Appendix 3), privacy invasion with an adapted three-item scale from Ayyagari et al. (2011), uncertainty with a three-item scale from Johnson et al. (2008), and fear with a two-item scale from Loyd and Gressard (1984). Creepiness, privacy invasion, uncertainty, and fear were measured on seven-point scales ranging from 1, strongly disagree, to 7, strongly agree. Privacy concerns were measured with an adapted four-item scale from Lwin et al. (2007) ranging from 1, not at all concerned, to 7, extremely concerned. Finally, trust in the technology was measured with a three-item scale from Thomson (2006) ranging from 1, not at all, to 7, very much.

4.2.2. Results

4.2.2.1. Factor analysis. The Kaiser-Meyer-Olkin (KMO) criterion was .97, which is above the recommended value of .60, demonstrating that the individual items shared enough common variance to conduct an EFA. The Bartlett test of sphericity was significant as well (χ^2 (465) = 7311.16, $p < .001$). To assess the dimensionality of the creepiness construct, we performed a principal component analysis with varimax rotation and evaluated the eigenvalues (Cattell, 1966). The scree plot revealed a clear inflection point after the first factor, providing support for the anticipated one-factor conceptualization. Retaining more than one factor led to only marginal increases in explained variance, so we continued the further scale development process based on a one-factor solution (explained variance: one factor (46%), two factors (53%), three factors (57%), four factors (60%)).

Next, we selected those items with high and distinct loadings on this one factor (≥ .80). In addition, we sorted out items that did not clearly load on the feeling of creepiness factor. The final item set included seven items (see Table 1).

Next, a CFA was conducted to assess the goodness of fit of the target factor model by using a combination of different indices proposed by MacKenzie et al. (2011). The factor model has a CFI of .99 and an SRMR of .01, indicating a good fit. While the RMSEA (.07) is slightly above the recommended threshold value of .06, it still fulfills the criteria for an acceptable model fit (MacCallum et al., 1996). Moreover, the scale has high internal consistency with Cronbach's $\alpha = .96$.

4.2.2.2. Discriminant validity. We tested if the average variance extracted (AVE) for creepiness is greater than the square of the correlation between potentially overlapping constructs (MacKenzie et al., 2011). The AVE for creepiness (.78) is larger than the squared correlations with all alternative constructs (privacy invasion: .49; uncertainty: .17; fear: .64; privacy concerns: .29; trust: .28), attesting to the discriminant validity of the construct (Fornell & Larcker, 1981).

4.2.2.3. Cross-validation. Ultimately, we collected new data to cross-validate the developed construct with a new sample (MacKenzie et al., 2011). We recruited $N = 300$ non-owners of SHAs from the United Kingdom, United States, Ireland, Australia, and New Zealand (*age range* = [18,75], $M_{age} = 32.97$, $SD = 11.17$, 59.0% female). An analysis of the factor structure of the construct provided renewed support for the proposed single-factor solution (explained variance: one factor (48%), two factors (56%), three factors (60%), four factors (64%)). Next, we tried to re-establish the previously proposed final item set (Table 1). For this purpose, we calculated the factor loadings for all 31 items from the initial item pool and selected those items with distinct and high factor loadings (≥ .80). This procedure yielded eight items: the seven items of the proposed item set and one additional item ("This smart home assistant scares me"). We calculated factor loadings for the eight items, and we again selected those with factor loadings of ≥ .80. This step resulted in exactly the same item set that was already obtained from the previous data collection (Table 1). In sum, our approach was based on two independent data sets – those of the main study and the cross-validation – which resulted in a robust measurement instrument for the creepiness construct.

4.3. Study 3: mechanisms and effects of perceived creepiness

4.3.1. Design, participants, and procedure

The aim of Study 3 was to test the nomological validity of the creepiness construct and the relationships depicted in the conceptual model (see Fig. 1). To this end, we conducted an experimental study, which is an appropriate approach to isolate the effects of inhibitors as well as their technology-based determinants (Cenfetelli, 2004; Shank et al., 2019). Study 3 was conceptualized as a 2 (tangibility: low vs. high) x 2 (transparency: low vs. high) between-subjects experiment design. A total of $N = 553$ participants from the United Kingdom, United States, Ireland, Australia, and New Zealand (*age range* = [18,84], $M_{age} = 41.12$, $SD = 15.25$, 63.5% female) were recruited through the online platform Prolific. All participants were non-owners of SHAs and had not participated in Study 2.

After reading a general introduction, participants were randomly allocated to one of the four conditions. We used vignette descriptions as stimuli, which is a common approach for studying the effects of different technology designs (Benlian et al., 2019; Jörling et al., 2019). Similar to Study 2, the vignettes described a situation in which a person called Bobby reads an ad about a fictitious SHA called QUANTUM. Depending on the experimental condition, QUANTUM was described as an SHA that can be integrated into ceilings or walls (low tangibility) or as a speaker that can be placed anywhere in a room (high tangibility). As noted previously, this is a realistic manipulation of tangibility, as recent developments allow SHAs to be integrated into everyday objects.

After being exposed to the ad, participants read that Bobby buys and installs QUANTUM, then asks the SHA for a recommendation of where to go for the next summer holidays. While QUANTUM recommends Tenerife as a destination, the rationale for this recommendation differs across the experimental conditions. That is, the SHA either declares that the algorithms and processes that led to this suggestion are part of trade secret regulations and cannot be disclosed to the user (low transparency) or that they are easily accessible for Bobby via the QUANTUM algorithm explainer app (high transparency). This manipulation is a realistic scenario, as algorithms and the underlying processes are often black boxes and well-kept company secrets. At the same time, recent research has raised the idea of providing users with human-in-the-loop systems such as personal app dashboards to increase the transparency of a device's underlying algorithms (Burton et al., 2020; Tene & Polonetsky, 2014; Watson & Nations, 2019). The experimental stimuli are summarized in Appendix 6.

4.3.2. Measures

We measured our main dependent variable, intention to use, with six items ($\alpha = .96$) adapted from Venkatesh and Bala (2008) and Jackson et al. (1997). Perceived ease of use was measured with three items adapted from Wixom and Todd (2005); ($\alpha = .85$), perceived usefulness with three items adapted from Limayem & Cheung (2007); ($\alpha = .92$), and resistance with four items adapted from Kim, & Kankanhalli (2009); ($\alpha = .95$). Creepiness was assessed with the items developed in Study 2 ($\alpha = .97$). We also included two manipulation checks to ensure that both design factors had been varied effectively (tangibility: "QUANTUM is a physical device that you can grab and take in your hand"; transparency: "QUANTUM can give you very specific answers about its working mechanisms"). All items used 7-point scales from 1, strongly disagree, to 7, strongly agree. Finally, we also measured participants' age, gender, and education (1 = "less than high school degree" to 6 = "graduate degree").

4.3.3. Results

As a proxy of effect sizes, Cohen's *d* along with the results from analyses of variance (ANOVA) and ordinary least squares (OLS) regressions are reported. We conducted maximum likelihood estimations for (conditional) mediation analyses and for the analyses of interaction effects, which is reported with the corresponding 95% confidence intervals based on 5000 bootstrap iterations (Hayes, 2013).

4.3.3.1. Manipulation check. The results revealed that both

Table 1
Selected Items and Factor Loadings.

Item label	Item	Loading
C-1	Having this smart home assistant in my room would creep me out.	0.89
C-2	This smart home assistant is creepy.	0.90
C-3	This smart home assistant makes me feel uncomfortable.	0.91
C-4	This smart home assistant gives me an eerie feeling.	0.87
C-5	This smart home assistant creeps me out.	0.90
C-6	I feel uneasy toward this smart home assistant.	0.89
C-7	I feel insecure around this smart home assistant.	0.84

manipulations were effective. Participants perceived the SHA as more transparent in the high transparency condition relative to participants in the low transparency condition ($M_{low\ trans} = 2.21$, $SD = 1.60$ vs. $M_{high\ trans} = 4.80$, $SD = 1.54$; $F(1, 596) = 403.97$, $p < .001$, $d = 1.10$). Additionally, participants in the high tangibility condition perceived the SHA as more tangible than participants in the low tangibility condition ($M_{low\ tan} = 2.32$, $SD = 1.66$ vs. $M_{high\ tan} = 4.91$, $SD = 1.87$; $F(1, 596) = 322.61$, $p < .001$, $d = 1.65$).

4.3.3.2. Hypotheses testing. First, we tested how specific design features of SHAs affect perceptions of creepiness. Consistent with H1, participants perceived QUANTUM as creepier when the transparency of the decision and recommendation algorithm was lower ($M_{low\ trans} = 5.44$, $SD = 1.51$ vs. $M_{high\ trans} = 4.89$, $SD = 1.68$; OLS regression: $B = -0.55$, $SE = .14$, $p < .001$, $d = -0.31$). In support of H2, participants perceived QUANTUM as creepier when its tangibility was lower, that is, when the device was integrated into walls and ceilings ($M_{low\ tan} = 4.28$, $SD = 1.58$ vs. $M_{high\ tan} = 3.75$, $SD = 1.44$; OLS regression: $B = -0.51$, $SE = .15$, $p < .001$, $d = -0.22$).

Next, we examined the effect of perceived creepiness on resistance. This analysis showed that the creepier participants perceived the SHA, the higher their resistance to using the SHA, supporting H3 (OLS regression including all conditions: $B = 0.57$, $SE = .03$, $p < .001$, $d = 1.11$). Considering the downstream effects of resistance, we find that all regression paths were significant at $p < .001$, except for the relationship between ease of use and usage intention ($p = .316$). In support of H4, resistance exerted a direct negative effect on usage intentions ($B = -0.22$, $SE = .05$) and negatively affected perceived usefulness (H5; $B = -0.60$, $SE = .03$) and ease of use (H6; $B = -0.20$, $SE = .03$). In line with H7, perceived usefulness exerted a positive effect on usage intention ($B = 0.71$, $SE = .03$). However, since ease of use did not significantly affect usage intention ($B = -0.03$, $SE = .03$), H8 had to be rejected. Finally, we tested the significance of the indirect effects of transparency and tangibility on usage intention through the proposed mediators – creepiness, resistance, perceived usefulness, and perceived ease of use. Except for the path through perceived ease of use, all indirect effects reached significance at 95% CI. Table 2 provides a detailed overview of all results.

5. Discussion

Study 3 provides support for our proposed conceptual model, demonstrating the relevance of perceived creepiness as both a predictor variable and a response variable. Concerning the former, the results confirm the nomological validity of the creepiness construct by showing its predictive power as an inhibitor as well as its distorting effects on enablers. Regarding the latter, the results confirm that creepiness is a relevant response variable. They demonstrate that perceptions of creepiness may arise in response to specific software- and hardware-side design features of SHAs, specifically, a lack of transparency on the software side and a lack of tangibility on the hardware side.

Table 2
Overview of the Results from Study 3.

Effect	B	SE	95% BC CI	
TRANS → CREEP	-0.55	.14	-0.81	-0.28
TANG → CREEP	-0.51	.15	-0.75	-0.22
CREEP → RESIST	0.57	.03	0.51	0.63
RESIST → PEOU	-0.20	.03	-0.26	-0.14
RESIST → PU	-0.60	.03	-0.65	-0.54
RESIST → UI	-0.22	.05	-0.27	-0.17
PEOU → UI	-0.03	.03	-0.09	0.03
PU → UI	0.71	.03	0.65	0.78
Indirect effects of transparency on usage intention				
TRANS → CREEP → RESIST → UI	0.07	.02	0.03	0.12
TRANS → CREEP → RESIST → PEOU → UI	- 0.00	.00	-0.01	0.00
TRANS → CREEP → RESIST → PU → UI	0.13	.04	0.07	0.21
Indirect effects of tangibility on usage intention				
TANG → CREEP → RESIST → UI	0.06	.02	0.03	0.11
TANG → CREEP → RESIST → PEOU → UI	- 0.00	.00	-0.01	0.00
TANG → CREEP → RESIST → PU → UI	0.12	.04	0.05	0.19

Note. TRANS = Transparency (1 = low, 2 = high); TANG = Tangibility (1 = low, 2 = high); CREEP = Perceived Creepiness (1 = low – 7 = high); RESIST = Resistance (1 = low – 7 = high); PU = Perceived Usefulness (1 = low – 7 = high); PEOU = Perceived Ease of Use (1 = low – 7 = high); UI = Usage Intention (1 = low – 7 = high); 95% BC CI: bias-corrected 95% confidence intervals based on 5000 bootstrap-iterations.

5.1. Study 4: focus group study

Study 3 provides evidence regarding the direction and strength of the hypothesized relationships. An additional focus group study delved further into the actual underlying behavioral dynamics, further enhancing our understanding (Maier et al., 2023; Venkatesh et al., 2013). The objectives of our focus group study were: a) elucidating the nuances of people's resistance reactions to the perceived creepiness of SHAs, and b) exploring SHA design ideas that could mitigate perceived creepiness.

5.1.1. Design, participants, procedure

To identify suitable participants (non-users who perceive SHAs as creepy), we used a screening survey, widely disseminated among our peers (for details on this and other focus group materials see Appendices 7 and 8). We followed Krueger and Casey's (2014) recommendation of involving 6–8 participants to ensure data saturation and effectively manage focus group dynamics. We selected six participants (average age: $M = 33.83$ years, $SD = 6.71$; gender: 4 female), which allowed us to gain insight into the behavioral dynamics underlying the perception of SHAs as creepy and the subsequent resistance to using them.

We developed an execution protocol in which our focus group session was broken into two main phases: 1) To foster a deep engagement with the subject matter, we initiated the session by encouraging participants to share instances from their daily lives where they found smart technology to be creepy. Participants also viewed a professionally produced video featuring human interactions with an SHA characterized by low levels of transparency and tangibility. 2) Subsequently, we conducted two rounds of individual brainstorming sessions and group discussions. The core topics of these conversations were the behavioral dynamics of resistance to SHAs due to perceptions of creepiness, the triggering software and hardware design features, and ways in which SHA vendors could design their products to alleviate potential perceptions of creepiness. The focus group was conducted virtually using MS Teams and the Mural App. The lead author acted as moderator, with two co-authors providing support. The focus group session was both video-recorded and supplemented with the research team's handwritten notes. In total, the focus group discussion lasted one hour and 41 min.

5.1.2. Data analysis and results

In line with similar focus group studies (e.g., Shi et al., 2020), we employed axial coding to analyze the data, following Strauss and Corbin (1990). Axial coding allowed us to identify key themes, patterns, and connections across the data. The author team organized the initial codes and grouped them into overarching categories and subthemes, enabling a deeper understanding of the participants' viewpoints and experiences. This allowed us to extract meaningful insights from the focus group discussions. To guide this coding process, we applied the following two overarching questions: 1) "What nuanced resistance behaviors arise when people perceive creepiness in SHAs?" 2) "What design-side actions could SHA vendors take to mitigate the perceived creepiness of SHAs and enhance their appeal for usage?".

Regarding the first question, eight distinct behavioral patterns emerged from our focus group study. Answers to the second question revealed nine recommendations for vendors – four on the hardware side and five on the software side – to mitigate potential perceptions of SHA creepiness and enhance their appeal. Table 3 provides a summary of our focus group results.

6. Discussion

We conducted a series of four distinct, complementary studies to explore the role of perceived creepiness in influencing individuals' resistance to SHAs. One pre-study used an inductive qualitative approach to offer preliminary, exploratory insights into the notion of "creepiness" in relation to SHAs. Subsequently, we devised Study 2 to develop a robust measurement tool to assess perceived creepiness. Next, in Study 3, we scrutinized the nomological validity of the creepiness construct within a broader conceptual model. Within this conceptual model, we hypothesized relationships between specific design-side features of SHAs, namely, software-side transparency (H1) and hardware-side tangibility (H2) and the perceived creepiness experienced by users. Furthermore, we created hypotheses about the downstream consequences of perceived creepiness on resistance (H3) and intention to use (H4), as well as the potentially distorting effects of perceived creepiness on enablers such as perceived usefulness (H5 and H7) and perceived ease of use (H6 and H8). We found empirical support for most of our hypotheses, except for H8. Our results underscore the relevance of perceived creepiness as both a predictor variable and a response variable. Concerning the latter role, our results substantiate the assertion that perceptions of creepiness manifest in response to specific software- and hardware-side design features of SHAs, specifically, a dearth of transparency on the software side and a lack of tangibility on the hardware side (as posited in H1 and H2). Moreover, our findings support the nomological validity of the creepiness construct by establishing its predictive capacity as an inhibitor (H3 and H4) and by elucidating its capacity to distort enabling factors (H5 - H8).

Finally, we conducted a focus group study (Study 4) to enhance our understanding of the behavioral dynamics linked to individuals' responses to perceived creepiness in the context of SHAs, broadening the scope of our findings beyond the sole consideration of usage intentions. This supplementary inquiry uncovered eight nuanced behavioral patterns that emerge as explicit responses to the perception of creepiness in the context of SHAs. These responses include, among others, usage restrictions, general refusal to use, behavior modification, negative word-of-mouth, as well as negative spillover effects on SHA vendors and other smart products. Furthermore, we explored potential design-side interventions that SHA vendors can undertake to mitigate the perceived creepiness associated with their products. We discovered nine such interventions that directly address both hardware- and software-side design attributes of SHAs. In sum, our research results illuminate a striking connection between the degree of tangibility on the hardware side, the level of transparency on the software side, and the likelihood of individuals perceiving SHAs as "creepy" and subsequently resisting the adoption and usage of SHAs.

Prior research has not extensively explored the specific aspect of software-side transparency in relationship to perceived creepiness and SHAs. While some evidence indicates that in certain settings, such as algorithm-based stocking recommendations in retailing, people may place more trust in an algorithm when they have no insight into its inner workings (Martinez, 2023), our findings align with the broader body of research in the field of consumer-oriented digital and AI-based technologies as well as SHAs (e.g., Benlian et al., 2019; Dwivedi et al., 2021; Recker et al., 2021; Shin et al., 2022; Watson & Nations, 2019). That is, we find that when algorithms lack transparency regarding their inner workings (e.g., data lineage) and the results they generate (e.g., recommendations), it can adversely affect users' perceptions. These adverse perceptions can lead to skepticism, discomfort, and user strain (Benlian et al., 2019; Watson & Nations, 2019). However, increasing algorithmic transparency may help build user confidence and acceptance (e.g., Dwivedi et al., 2021; Shin et al., 2022).

On the hardware side, the notion of tangibility in the context of SHAs

Table 3
Focus Group Results.

Category	Category Description	Example Quote
1) What nuanced resistance behaviors emerge when individuals perceive creepiness in SHAs?		
Usage restrictions	Constraints placed on the specific functions, features, locations, or periods during which the SHA can be used.	*"I would only place the device in certain rooms where I can be sure that what I say may also be heard by the device."* *"This also goes hand in hand with the fact that I would only use it* [SHA] *for very limited purposes, for example, only in the kitchen to set a timer."*
General refusal of use	A categorical rejection of the use of SHAs in the household.	*"I would really want to make sure that I just don't have any smart home assistants in my entire household."*
Information gathering	Actively seeking more information about the SHA device and its provider to make informed decisions.	*"I would do some research on the manufacturer, trying to find out if the company is actually trustworthy."*
Behavior modification	Modifying one's behavior, such as avoiding certain topics or changing communication patterns, in the presence of an SHA.	*"I would avoid certain topics of conversation. If I knew I was sitting with friends and felt like a device was listening in, that would make me just not talk about certain topics."*
Applying coping strategies	Seeking peer support, deliberately avoiding SHAs, or checking for their presence to address discomfort.	*"I would start googling and see if others have had similar experiences, such as looking at Amazon reviews or discussing the issue on Twitter."* *"I would simply check regularly to see if there are any such devices in the room."*
Negative word of mouth	Sharing negative opinions and experiences with peers, potentially influencing their attitudes.	*"I would tell my peers about it, and those anecdotes would certainly have a negative connotation, which would then probably also have a negative effect on their attitudes."*
Negative spillover effects on other smart products	Only using/purchasing smart products if they do not have an integrated smart assistant.	*"The perceived creepiness would definitely also affect other connected devices, and as soon as another device is Wi-Fi-enabled, it would immediately trigger me and put me in a state of heightened vigilance."*
Negative spillover effects on provider firms	Avoid using or buying products/services from SHA provider firms.	*"This would also result in a lack of comprehension regarding the company. It would make me quite angry, and this would also impact the provider, ultimately resulting in a negative perception of the company."*
2) What design-side actions could SHA vendors take to mitigate the perceived creepiness of SHAs and enhance their appeal for usage?		
Hardware-side		
Visual status cues	Implementation of visual status cues, such as different colored light signals or icons, or screens, that clearly signal to the user when the device is activated and recording.	*"Vendors should create transparency on a physical level, for example, via light signals or something similar, so that I see the assistant is active, and I am aware that it is listening."*

(continued on next page)

Table 3 (*continued*)

Category	Category Description	Example Quote
Auditory status cues	Use of audible signals, such as sounds before activation or asking for permission to listen, to alert users to the device's status.	*"It would need a kind of announcement whenever one* [SHA] *is in the room. For example, I also find it creepy with people when someone suddenly speaks, and I didn't know the person was in the room."*
Utilization of buttons/ tangibles	Installation of physical on/ off buttons for easy device deactivation and power/Wi-Fi disconnection.	*"What I would like to see is a physical interaction option – a real button that I can press to signal, 'Okay, now you should listen to me.' Only then should voice control be activated, and the device should not be continuously listening."*
Adding human-like cues	Incorporating design elements that make the SHA feel more human and friendly.	*"I would appreciate more humanization, as it would create a stronger sense of having a friendly counterpart. In other words, it would make the system feel like a companion that stores and accesses information for you."*
Software-side		
Enabling access to recommendation algorithms	Providing means for users to understand how data is used for recommendations, possibly through user-friendly dashboards.	*"When queried, the device should elucidate the process of data collection and its subsequent utilization. Think of it as a sort of digital logbook that can subsequently provide information such as this: 'On a specific day, you mentioned your preferences for visiting the Canary Islands, enjoying beach vacations, and cycling. This is why I suggested Tenerife as your next holiday destination'."*
Embedding proactive questioning of users	SHA proactively engages in a conversation with the user to define when it should be active, seeking permission.	*"I believe it would be beneficial to establish a dialogue with the device, wherein it proactively requests permission to listen and explains its intentions. This way, I can make informed decisions, choosing to allow it to listen at specific times or decline altogether."*
Embedding restriction options	Integrating restriction choices, like enabling SHAs to utilize personal data for recommendations versus opting for public data pools (e.g., online reviews for travel suggestions), or configuring downtime periods when the device should be inactive.	*"It would be good if there existed a function through which I could specify that an SHA's recommendations are derived from either personalized information or readily accessible information."*
Attainment of third-party certification	Describes attaining certification from an independent oversight authority ensuring SHA algorithm compliance and guaranteeing specific standards.	*"…it would greatly benefit me to have an institution that regularly evaluates the algorithm and provides a seal that signifies that the device operates in the best interests of its users. In other words, a third party that assesses it objectively and has full access to the programming."*
Commitment to user-centric algorithm programming	Describes the credible commitment by the manufacturer to ensure that the algorithms programmed in the SHA always act in the best interest of the user.	*"…a self-commitment* [from the SHA provider] *that instills in me a confidence level compelling enough to make me select this device above all others."*

has not yet been examined. However, our findings substantiate a popular idea that the absence of tangible elements can exert an adverse impact on individuals' perceptions of a company's offerings. Scholars in the domains of service and innovation research have previously discussed this phenomenon (e.g., Bardhi & Eckhardt, 2017; Laroche et al., 2004; Murray & Schlacter, 1990), which is particularly pronounced when a user is evaluating offerings that work with the user in close psychological proximity (Ding & Keh, 2017). This characteristic particularly applies to SHAs as they are integrated into the most intimate areas of our lives – our homes. In contrast, and in line with our findings, incorporating elements that enhance spatial presence, like tangible elements (e.g., visual/auditory status cues or physical interfaces such as buttons), has been found to increase emotional engagement, resulting in a more positive perception of the SHA (Heller et al., 2021).

In addition, our findings unveil the predictive capacity of perceived creepiness as an inhibitor to the adoption of SHAs. We not only demonstrate its direct negative impact on usage intentions but also its biasing effect on potentially positive aspects, such as perceived usefulness and perceived ease of use. This aligns with Cenfetelli's (2004) dual-factor model of technology resistance which highlights the role of inhibitors in affecting technology usage intentions directly, as well as indirectly by moderating enablers. Empirical evidence from other studies across various technology contexts, such as social media (Sullivan & Koh, 2019) and telehealth (Tsai et al., 2019), further supports this notion.

6.1. Theoretical contributions and implications

Our findings make several contributions to the literature. First, by investigating consumers' emotional and attitudinal responses within the context of acceptance and resistance, this study contributes to the existing literature focusing on the adverse aspects of smart technology (e.g., Brous et al., 2020; Cenfetelli, 2004; Ilie & Turel, 2020; Jain et al., 2023; Marikyan et al., 2019; Vimalkumar et al., 2021). In particular, our findings contribute by offering a nuanced perspective on individual-level resistance to SHAs. That is, we expand the existing understanding of psychological barriers to SHAs by showing that consumer resistance arises not only from factors such as cost, perceived risk, and unreliability (Balta-Ozkan et al., 2013; Chouk & Mani, 2019; Lau et al., 2018; Wilson et al., 2017), but also from a perception of creepiness.

Second, this research contributes to the IS literature on the dual-factor model of technology resistance by emphasizing both enabling and inhibiting beliefs, the often-overlooked dual perspective of user considerations during adoption processes. By investigating these opposing types of beliefs and their interplay, we provide a comprehensive view of potential obstacles (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011). More precisely, we demonstrate that resistance to SHAs has a detrimental effect on perceived usefulness, a factor that has been consistently identified as a crucial enabler for adoption (Fernandes & Oliveira, 2021; Marikyan et al., 2019; Shin et al., 2018). This underscores the adverse effects of resistance beliefs. Moreover, our study explores these effects in a social group often overlooked in IS research – resistant non-users. While most resistance studies focus on organizational contexts and mandated technology implementations, our work delves into voluntary usage contexts, where users have complete freedom to choose whether to adopt or resist a new technology (Van Offenbeek et al., 2013).

Third, this research contributes by identifying two hardware- and software-side design features of SHAs – transparency and tangibility – the lack or low level of which may trigger perceived creepiness and undermine usage intentions. As mentioned earlier, the results of this research suggest that the perception of SHAs is two-sided. While SHAs may possess features that are perceived as useful and easy to use, their potentially creepy nature may cause resistance, undermining the intention to use them. Thus, while SHAs' recommendations may be easy to obtain as well as accurate and useful, individuals may consider SHAs creepy if their inner workings are unclear, and if the device lacks a strong spatial presence. These findings also contribute to the emerging research stream on a design toolbox for smart or digital technologies. Mani and Chouk (2018) find that digital technologies should be designed in an intuitive and easy-to-use manner to mitigate resistance, Benlian et al. (2019) argue that anthropomorphic design features can alleviate the intrusive effects of digital technologies, and Tereschenko et al. (2022) show that adding affiliative humor to communication with smart home technologies can increase perceived trustworthiness, and thus may drive acceptance. The results of the present work add to this stream of research by showing that feelings of creepiness and ensuing resistance can be mitigated by unmasking these technologies, that is, increasing their hardware-side tangibility and the software-side transparency of the inner workings of underlying algorithms and processes.

Finally, our work adds to an emerging body of research on creepiness in technology contexts (e.g., Sullivan et al., 2020; Tene & Polonetsky, 2014; Watson & Nations, 2019) by offering novel insights into the nature of creepiness within the domain of smart, algorithm-driven technologies. Although this study examines creepiness in the specific context of SHAs, its findings hold broader implications. On the one hand, the cyber-physical nature of SHAs and the characteristics that contribute to feelings of creepiness (e.g., a lack of transparency regarding the underlying decision algorithms, and a lack of tangibility due to increasingly embedded devices) may also apply to many other smart consumer technologies. On the other hand, the increasing integration of devices into the environment and the reliance on complex and opaque algorithms reflect broader technological trends that extend beyond SHAs. On a more general level, the findings demonstrate that smart technology may give rise to new inhibitors – in the present case, creepiness. In the past, IS research has greatly benefitted from artifact-centered studies and the discovery of artifact-specific inhibitors (see for example Craig et al., 2019; Mahmud et al., 2017).

6.2. Implications for practice

Our findings also yield significant implications for SHA vendors, particularly in the realm of technological design. By uncovering tangibility and transparency as hardware- and software-side design features of SHAs that may trigger perceived creepiness if they are at low levels, this work develops clear and actionable guidelines for optimizing the design of SHAs.

Regarding tangibility, current smart home design trends indicate that SHAs are increasingly disappearing as standalone physical devices. Rather, designers are integrating them into everyday household objects such as mirrors, or into the structural components of walls or ceilings. While fully embedding SHAs may theoretically enable more seamless interaction, it may also heighten the risk of users feeling uncomfortable and creeped out. Therefore, companies may need to strike a balance between these two sides when designing future SHAs. Designers must explore how to provide tangible elements that users can connect with even when an SHA is fully integrated into the living environment. Our focus group study has led to several ideas for technology design that SHA vendors could directly apply to their devices. For example, to enhance the perceived tangibility of SHAs and improve their spatial presence, SHA vendors should incorporate tangible elements, such as visual or auditory status cues. These cues could include different colored light signals or icons on screens that indicate when the device is active. Auditory status cues before activation or dedicated requests for permission to listen can alert users to the device's status. Vendors should also consider incorporating physical on/off buttons so users can easily deactivate the device and disconnect it from power and Wi-Fi.

On the software side, our findings strongly support the idea that SHA design should prioritize algorithm transparency, enabling every user to follow the inner workings of algorithms and the results they generate. Based on our focus group study, we can outline a set of actions that providers can take to achieve this goal. First, vendors should provide SHA users with access to recommendation algorithms via systems such as user-friendly apps and dashboards that explain how the SHA came to a particular decision or recommendation. Moreover, incorporating proactive engagement with users, where the SHA initiates a conversation to determine when it should be active, can enhance transparency. Vendors should also offer configuration choices, allowing SHAs to use personal data for recommendations or draw from public data sources (e.g., publicly available online reviews for travel suggestions). Furthermore, vendors should pursue certification through a reputable independent oversight authority or obtain a favorable assessment from trusted institutions, such as the Mozilla Foundation, to ensure SHA algorithm compliance and adherence to specific standards. Such a commitment should prioritize user-centric algorithm programming and testing, ensuring that the algorithms within the SHA consistently act in the best interest of the user.

In sum, our findings regarding the tangibility and transparency of SHAs may help companies design and calibrate their devices to avoid crossing the line into creepiness.

6.3. Limitations and future research directions

Our work has limitations that warrant further research. Firstly, the analysis and coding of our qualitative studies 1 and 4 may be prone to researcher bias and personal interpretations, a common limitation in qualitatively driven constructivist research often employed in multi- or mixed-method studies (Onwuegbuzie & Leech, 2007).

Second, the measurement instrument we developed was only tested in a controlled online setting with participants from English-speaking countries. While this analysis confirmed the reliability and validity of the scale, future research may test its ecological validity in real-life settings and eventually extend it to other cultural contexts.

Third, our experimental Study 3 was based on hypothetical scenarios and was tested with an online sample, which is usually a limitation to ecological validity (Benlian et al., 2019). Future studies should therefore replicate the findings in realistic field study settings to ensure the generalizability of the findings of this work.

Apart from these methodological limitations, future researchers may also want to enhance the scope of the conceptual framework. Identifying further detrimental mechanisms would be of particular interest. On the one hand, such studies can focus, the way we did, on specific design features of SHAs, further advancing the design toolbox for smart or digital technologies. On the other hand, researchers could examine the deeper mechanisms of how users transfer negative perceptions across different entities. Henkens et al. (2020) find that for smart products, negative perceptions mainly apply to the entity most present to the user, that is, the material, visible product rather than the provider. Thus, providers may enjoy some immunity from negative spill-over effects as they are only second in line. However, it may be interesting to examine if and how this effect unfolds when the material product vanishes, as with built-in SHAs. In this scenario, negative perceptions may extend beyond the product sphere to the provider since users can no longer focus their ire on a physical device.

Furthermore, since different innovations elicit diverging resistance responses (e.g., Kleijnen et al., 2009), future research could delve deeper into scrutinizing the distinct taxonomy of resistance reactions triggered by the perceived creepiness of SHAs. Consider the tripartite framework of hierarchical resistance responses posited by Kleijnen et al. (2009). Future research may further explore the characteristics of the dominant resistance response caused by creepiness, namely: (1) postponement (temporary delay of adoption decision), (2) rejection (conscious choice not to adopt), or (3) opposition (active opposition aimed at influencing others' adoption decisions).

Finally, future research could conduct a large-scale survey to examine the interplay of specific SHA characteristics and other key constructs identified in our pre-study and beyond. Such a study could test more explicitly how different inhibitors and technology-side characteristics influence or overrule enablers. In this regard, distinguishing between "resistance by mind" (technology characteristics and inhibitors that compromise the perceived usefulness of SHAs) and "resistance by design" (technology characteristics and inhibitors that compromise the perceived ease of use of SHAs) could be a promising path for future research.

7. Conclusion

SHAs are a breakthrough in the digitization of our daily lives. Run by increasingly powerful software and remotely operated by voice control, they offer many opportunities but may also trigger resistance. Our investigation elucidates the understanding of the novel inhibitor *perceived creepiness* and its effect on resistance towards SHAs. Through four complementary studies, we investigate the concept of creepiness, create a measurement tool, examine the triggers and consequences of perceived creepiness, and explore actual behavioral dynamics surrounding it. Additionally, we carve out potential mitigating design-side actions for vendors. In sum, we shed light on the effect of perceived creepiness on resistance to SHAs, while also contributing to a deeper comprehension of the intricate mechanisms that underlie this relationship. We believe that our insights can stimulate future research in this area, just as we hope that practitioners will find inspiration for viable design solutions for smart technologies that effectively reduce user resistance and drive overall adoption.

CRediT authorship contribution statement

Stefan Raff: Conceptualization, Methodology, Investigation, Formal analysis, Resources, Supervision, Project administration, Writing – original draft preparation, Writing – review & editing. **Stefan Rose:** Conceptualization, Writing – review & editing, Project administration, Supervision. **Tin Huynh:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijinfomgt.2023.102720.

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