Smartness unleashed: a multilevel model for understanding consumers' perceptions and adoption across a myriad of smart offerings

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Abstract

Purpose – Consumers' perceptions of product intelligence affect their willingness to accept smart offerings. This paper explores how people perceive various smart products based on their smartness profiles, composed of five distinct smartness facets. Additionally, the study investigates how these perceptions of product intelligence impact consumers' evaluation of factors that either promote or impede the adoption of smart products. These factors are examined as potential mediators in the adoption process. This paper aims to determine if the value-based adoption model can be applied to a broad range of smart service systems.

Design/methodology/approach – Consumers assessed one of 28 smart products in a scenario-based quantitative study. Multilevel structural equation modeling (SEM) is used to test the conceptual model, taking the nested data structure into account.

Findings – The findings show that product smartness essentially enhances usage intention via adoption drivers (enjoyment and usefulness) and reduces usage intention via adoption barriers (intrusiveness). In particular, the ability to interact in a humanlike manner increases the benefits consumers perceive, which in turn increases consumer acceptance. Only the smartness characteristic of awareness impairs usage intention, mediated by the perceived benefits of enjoyment and usefulness.

Originality/value – In contrast to previous research, which usually focuses on single smart products, this work examines a variety of different products, which allows for better transferability of the results to other smart offerings. Furthermore, prior research has mainly focused on single facets of product smartness or researched smartness on an aggregated level. By considering the consumer perception of each smartness facet, the authors gain deeper insights into the perceptual differences regarding product smartness and how this affects technology adoption via conflicting key acceptance drivers and barriers.

Keywords Smart products, Multilevel modeling, Smartness characteristics, Value-based adoption model, Technology acceptance, Smart service systems

Paper type Research paper

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Introduction

Advances in information technology amplify the conversion from conventional products to so-called "smart products" (Bilstein and Stummer, 2020; Dawid *et al.*, 2017). Smart products are physical devices that have embedded technology and are capable of connecting to the internet or other devices to provide advanced functionality, automation and connectivity (e.g. Hoffman and Novak, 2015; Mayer *et al.*, 2011; Novales *et al.*, 2016; Raff *et al.*, 2020). Often, smart products are part of a product system (Porter and Heppelmann, 2014) and their functions enable service offerings within a larger service ecosystem (Raff *et al.*, 2020). In smart service systems, smart products link service providers and consumers, enabling value co-creation by "obtaining contextual data from the field, analyzing these data, automatically making decisions and taking action" (Beverungen *et al.*, 2019, p. 8).

Predictions regarding the business potential of smart products and market growth are high, e.g. for the global smart home comfort and appliances market, which includes products such as heating and lighting systems (IDC, 2022). In 2021, this market grew by approximately 12% as compared to 2020 and is anticipated to maintain steady growth at a rate of 10% over the next five years.

Smart products have a variety of advantages for consumers such as facilitating everyday life (Baber, 1996) and creating added value beyond the pure product benefit (Mayer *et al.*, 2011). At the same time, people are concerned about their privacy as worldwide surveys show. Individuals are alarmed about their (digital) privacy and might not readily accept online privacy risks merely for the sake of convenience (NortonLiveLock, 2020). Belk (2017) puts the situation in a nutshell by pointing out that consumers are simultaneously anxious about and fascinated by smart technology.

In addition to the established knowledge about acceptance barriers for technology products, such as performance and effort expectancy (Venkatesh *et al.*, 2003), additional factors affecting the acceptance of smart products have been identified. However, these findings are often limited to single products (e.g. Jörling *et al.*, 2020; Mani and Chouk, 2017, 2018), requiring a thorough understanding of the key factors influencing consumer adoption of various smart products. In this regard, our research provides insights to understand consumer preferences by investigating a myriad of smart products. This study aims to shed light on how consumers assess the product intelligence of smart products and how this affects product acceptance, via benefits from and the sacrifices for using smart products. This holistic approach contributes to the literature by allowing the generalizability of a value-based adoption model across different smart products.

Furthermore, the individual studies mainly focus on a specific smart product (e.g. Henkens *et al.*, 2021; Park and Lee, 2014) or a single facet of smartness (e.g. Chouk and Mani, 2022; Hoffman and Novak, 2018; Lucia-Palacios and Pérez-López, 2021; Schweitzer and Van den Hende, 2016). Research that addresses the differences between smart products, especially those at concerned with the extent or manifestations of such differences, underlines the difficulty of capturing product intelligence (Henkens *et al.*, 2021; Rijsdijk and Hultink, 2009). By considering the contribution of each smartness facet instead of an aggregate view, we extend the existing knowledge about the influence of product intelligence by gaining deeper insights into perceptual differences.

Previous research has mostly examined product smartness influence by manipulating it in experiments (e.g. Henkens *et al.*, 2021; Rijsdijk and Hultink, 2009; Kaldewei and Stummer, 2018). By measuring the product intelligence perception of existing smart products instead, the present study allows for a more realistic consumer assessment, thus gaining deeper insights into the perceptual differences (Tourangeau *et al.*, 2000). These insights are of importance, as examining the acceptance of smart products is crucial for businesses attempting to remain competitive and capitalize on the significant market potential of smart products (Bilstein and Stummer, 2023). In sum, our study provides replicability across smart products and a multidimensional conceptualization of product smartness to achieve differentiated insight into consumers' perceptions.

Theoretical background and conceptual framework

Technical characteristics of product smartness

Even though smart products are still considered an emerging topic, there has been a steady increase in studies over the past two decades (Raff *et al.*, 2020). One potential problem is that various terms such as "smart product" (e.g. Beverungen *et al.*, 2019; Dawid *et al.*, 2017), "smart object" (e.g. Novak and Hoffman, 2018), "smart device" (e.g. Schweitzer *et al.*, 2019), "intelligent product" (e.g. Holler *et al.*, 2016) and "digitized artifact" (e.g. Herterich and Mikusz, 2016) have been introduced to outline an identical concept. These terms have in common that (information) technology is integrated into a physical object. In consequence, purely digital products (i.e. digital services) are not considered smart products (Novales *et al.*, 2016; Raff *et al.*, 2020).

Smart products are characterized as being able to act proactively and autonomously, context-aware, able to adapt to their environment and able to cooperate with other products (Raff *et al.*, 2020). Thus, they combine a variety of capabilities that non-smart products accomplish only in parts. To render these capabilities on the part of smart products possible, the following three technologies are used: First, sensor technology enables smart products to gather data. Sensor data includes any information products can perceive about themselves, their condition and their environment (e.g. Beverungen *et al.*, 2019; Mani and Chouk, 2017). Second, due to network technology, smart products can receive information as well as communicate and interact with other entities (e.g. Beverungen *et al.*, 2019; Porter and Heppelmann, 2014). Third, computing technology allows the organization, processing and utilization of data for functional purposes (e.g. Atzori *et al.*, 2010; Mayer *et al.*, 2011).

Manifestations of product smartness

If a product can be classified as a smart product, the question of how the smartness expresses itself arises. Early definitions did not define the "smartness" that information technology enables (e.g. Baber, 1996; Dhebar, 1996). There are only a few studies that provide distinct conceptualizations of the dimensionality of product smartness (see Table 1). All studies are based on the initial conceptualization of product intelligence proposed by Rijsdijk *et al.* (2007): autonomy, adaptability, reactivity, the ability to cooperate, humanlike interaction, personality and multifunctionality. According to Rijsdijk and Hultink (2009), the overall intelligence of a product can be assessed based on the extent to which it exhibits these capabilities. They posit that "smart products possess one or more of these dimensions to a lesser or higher degree" (p. 25).

In light of advancing developments in information technology, Henkens *et al.* (2021) propose the subsequent four constitutive smartness characteristics as a revised conceptualization of product smartness: *Actuation* refers to the smart product's "ability to decide and act independently based on computational processes" (Henkens *et al.*, 2021, p. 428; among others Hoffman and Novak, 2018; Verhoef *et al.*, 2017). The characteristic of *dynamism* refers to a smart product being able to learn as well as adapt (Henkens *et al.*, 2021; among others Beverungen *et al.*, 2019; Hoffman and Novak, 2018). The smartness characteristic of *awareness* refers to a smart product's "ability to sense information [..] and/or its surroundings" (Henkens *et al.*, 2021, p. 428; among others Töytäri *et al.*, 2018; Wünderlich *et al.*, 2015). This characteristic is enabled through sensor technology, allowing the products to perceive information. Lastly, they propose the smartness characteristic of *connectivity*, "which encompasses the ability to connect – through the internet of Things (IoT) – different actors" (Henkens *et al.*, 2021, p. 427, among others; Atzori *et al.*, 2010; Verhoef *et al.*, 2017).

Table 1. Overview of product smartness conceptualizations

Source	Smartness characteristic/dimension 1	2	3	4	5	6	7
Rijsdijk *et al.* (2007)	Autonomy	Ability to learn	Reactivity	Ability to cooperate	Humanlike interaction	Personality	–
Rijsdijk and Hultink (2009)	Autonomy	Ability to learn	Reactivity	Ability to cooperate	Humanlike interaction*	Personality*	Multifunctionality
Park and Lee (2014)	Autonomy	Ability to learn	Reactivity	Ability to cooperate	Humanlike interaction	–	Multifunctionality
Kaldewei and Stummer (2018)	Autonomy	Ability to learn	Reactivity	Ability to cooperate	Humanlike interaction	–	Multifunctionality
Lee and Shin (2018)	Autonomy	Adaptability	Reactivity	Ability to cooperate	–	–	Multifunctionality
Li *et al.* (2023)	Intelligence attribute		Connection attribute		–	–	–
Rhiu and Yun (2018)	Autonomy	Adaptability		Connectivity	Personalization		Multifunctionality
Henkens *et al.* (2021)	Actuation	Dynamism	Awareness	Connectivity	–	–	–
This study	Actuation	Dynamism	Awareness	Connectivity	Humanlike interaction	–	–

Note(s): *Smartness characteristic/dimension not empirically investigated in the study
Source(s): Table created by the authors

As (information) technology continues to advance, products become more and more humanlike (Foehr and Germelmann, 2020). There are different views in research on the inclusion of human characteristics as a sub-dimension of product smartness. In their conceptualization of product smartness, Rijsdijk *et al.* (2007) propose the dimensions of humanlike interaction, which "concerns the degree to which the product communicates and interacts with the user in a natural, human way" (p. 343). In contrast, Novak and Hoffman (2018) postulate that including the smartness dimensions of *humanlike interaction* and *personality* is not a question of "not yet" but, rather, one of "not at all". According to these researchers, products do not have the qualities of personality and humanlike interaction, which are needed to be considered "smart". In a similar vein, Henkens *et al.* (2021) disregard these qualities of product smartness as well.

However, a multitude of products have the ability to interact in a humanlike manner to a certain extent. In particular, the increasing implementation of voice assistants is making interaction and communication with products more humanlike (Böhm *et al.*, 2022). However, as some smart products possess the ability of humanlike interaction while others do not, it is considered to be a smartness dimension rather than a constitutive characteristic of product intelligence.

The initial smartness dimensions were investigated in several studies. For instance, Rijsdijk *et al.* (2007) report positive effects on the part of overall product intelligence on consumer satisfaction, which were mediated by relative advantage and compatibility. In addition, there was a negative mediating effect via complexity. In their 2009 study, Rijsdijk and Hultink distinguish between low and high levels of autonomy, adaptability and reactivity as well as between low, medium and high manifestations of multifunctionality and the ability to cooperate with other products. Their findings show that higher levels of product smartness have various positive and negative effects on consumer evaluations, which vary across smartness dimensions and smart products. For example, higher levels of all smartness dimensions cause higher levels of perceived risk, whereas the effects on relative advantage, compatibility and complexity vary.

Kaldewei and Stummer (2018) confirm the positive effect of the smartness dimensions on consumption values and product usage for three selected smart products. Their findings are in line with Park and Lee's (2014) examination of the relationships between perceived smartness, perceived value and user behavior in the form of consumer usage of smartphones. Lee and Shin (2018) also identify significant positive effects on the part of adaptability and multifunctionality on perceived smartness and consumer satisfaction.

By analyzing tweets, Rhiu and Yun (2018) examine the user experience of smartphones. Their study supports the notion of product smartness predominantly positively affecting user experience. Only multifunctionality and connectivity lead to unsatisfactory experiences in cases of, for example, low quality of function. In their study, Henkens *et al.* (2021) investigate how product smartness affects customer well-being. In their scenario-based experiment, they manipulate the smartness characteristics of a smart fridge. They find that customer well-being is higher with higher levels of smartness via customer engagement.

Even though there are already initial studies examining products with varying levels of (a selection of) smartness facets, a profound understanding of how consumers' perception of smartness differs across various smart products is missing. Studies focus on a single product; thus, their findings allow for only limited generalizability (e.g. Lee and Shin, 2018; Park and Lee, 2014). Furthermore, product intelligence was mostly/usually manipulated in various gradations (high/low or high/medium/low) instead of being measured as consumers perceive it (e.g. Henkens *et al.*, 2021; Rijsdijk and Hultink, 2009). While this may be appropriate for the respective research objectives, we believe that measuring product smartness on Likert-type scales provides a more nuanced insight into consumers' perceptions of product intelligence. By not manipulating product smartness, actual consumers' perceptions is measured, resulting in a more realistic and less biased evaluation compared to manipulation. Moreover, while other studies mainly examine variation in the overall smartness of a product (e.g. Henkens *et al.*, 2021; Rijsdijk *et al.*, 2007), we further suppose that the expression of the different product smartness facets is interesting, as the influence of the facets could be overlapping or even opposite.

To the best of our knowledge, our study is the first to consider the various smartness characteristics individually. It does not manipulate smartness. Rather, it measures how consumers perceive these smartness characteristics and provides a broader view by considering various products simultaneously (see Table 2).

Drivers of and barriers to smart product adoption

Given the tremendous growth of smart technologies, marketing researchers have studied them extensively, commonly focusing on outcomes such as engagement (e.g. Henkens *et al.*, 2021), well-being (e.g. Tikkanen *et al.*, 2023), resistance (e.g. Mani and Chouk, 2017, 2018; Chouk and Mani, 2019) and acceptance (e.g. Hubert *et al.*, 2019; Mayer *et al.*, 2011). In the context of smart product acceptance, researchers have identified and studied various consumer products, such as wearables (e.g. Cavdar Aksoy *et al.*, 2020; Tikkanen *et al.*, 2023), autonomous vehicles (e.g. König and Neumayr, 2017) and smart home technologies (e.g. Hubert *et al.*, 2019).

Existing literature has extended our understanding of what drives and obstructs consumer acceptance of smart products. In Table 3 we provide an overview of the literature on factors influencing smart product acceptance in terms of different dependent acceptance variables. To ensure comparability with this study, only quantitative studies were included. Furthermore, literature on smart services was disregarded as this study focuses on tangible products, technologies and their functionality. Even though smart products often include services and partly operate in ecosystems, this would increase the model complexity and is beyond the scope of this study.

We find that a growing body of research has focused on the impact that enjoyment and usefulness have on consumer adoption. Hubert *et al.* (2019) find usefulness to be a major adoption driver for smart home technology. Kim and Moon (2023) as well as Kowalczuk

Authors	Characteristics considered individually	Smartness not manipulated	Considers various products	Considers key mediators
Rijsdijk *et al.* (2007)		✓	✓	
Rijsdijk and Hultink (2009)	✓		✓	
Park and Lee (2014)	✓	✓		
Kaldewei and Stummer (2018)*	✓	✓	✓	
Lee and Shin (2018)	✓	✓		(✓)
Li *et al.* (2023)		✓		
Henkens *et al.* (2021)				✓
This study	✓	✓	✓	✓

Note(s): *No integrated consideration of the three products studied
Source(s): Table created by the authors

Table 2.
Overview of studies empirically examining product intelligence

Source	Research object	Dependent variable	Findings
Schweitzer and Van den Hende (2016)	Smart household objects	Adoption intention	Autonomous smart products are perceived as more *disempowering* than semi-autonomous smart products; adoption likelihood is negatively affected
Mani and Chouk (2017)	Smartwatch	Resistance	The results show that uselessness, price, *intrusiveness,* novelty, and self-efficacy have an impact on consumer resistance to smart products. In addition, privacy concerns affect intrusiveness and dependency affects privacy concerns
Kowalczuk (2018)	Smart speaker	Behavioral intention	Besides ease of use and *usefulness*, the quality and diversity of a system, its *enjoyment*, consumer's technology optimism, and risk strongly affect the acceptance of smart speakers, with enjoyment having the strongest effect
Hubert *et al.* (2019)	Smart home	Behavioral intention	The study highlights that compatibility and *usefulness* as the foremost determinants of use intention, with *usefulness* also mediating the effect of risk perception
Bölen (2020)	Smartwatch	Continuance intention	Bölen finds a significant positive effect of *usefulness* on attitude toward sports wearables and attitude of usage intention
Kim and Moon (2023)	Smart washing machine	Acceptance intention	While for full-time housewives especially *usefulness* significantly influences acceptance for employed females it is both *usefulness* and *enjoyment*
Li *et al.* (2023)	Smartphones, smartwatches	Adoption intention	Smart products can improve consumers' perceptions of the four motivations of meaning, capability, autonomy, and influence, which activate consumers' *psychological empowerment* and thus improve consumers' adoption intention
Lucia-Palacios and Perez-Lopez (2023)	Smart home voice assistant	Repurchase intention	*Usefulness,* coolness and interactivity show positive mediating effects between autonomy and experience, while *intrusiveness* has a negative mediating effect. The better the consumer's experience, the greater the repurchase intention

Note(s): Selected studies. The studies were chosen because of their relevance to the research objective
Source(s): Table created by the authors

Table 3. Overview of studies empirically researching drivers and barriers of smart product (non-)adoption

(2018) identify significant positive effects on the part of enjoyment and usefulness. Moreover, Kowalczuk (2018) identifies enjoyment as the strongest driver of smart speaker adoption.

Furthermore, there is growing attention being paid to the factors inhibiting smart product adoption. The influence of intrusiveness has been of particular interest. Mani and Chouk (2017) show that intrusiveness, among other factors, increases consumer resistance to smart products. Similarly, Lucia-Palacios and Pérez-López (2023) show that intrusiveness relates negatively to consumer experience, thus, lowering, repurchase intentions.

In addition, perceived control has been identified as an acceptance-influencing factor. A recent study by Smith *et al.* (2023) emphasizes how the automation of products, which is a key ability of smart products, decreases feelings of control, as previously shown by Schweitzer and Van den Hende (2016). In contrast to previous studies, which mainly focused on the effect of automation on control, respectively product acceptance, we simultaneously consider all smartness facets.

In research on the acceptance of smart products, the influence of various factors has been investigated, as Table 3 shows. We add to this research by conducting an empirical study investigating various smart products via a multilevel approach. This approach provides generalizability of the model across different smart products. Thereby, we analyze how the aforementioned five different facets of product smartness characteristics (individually and without manipulation) affect consumers' perceptions of the drivers (enjoyment and usefulness) and barriers (intrusiveness and control) of using smart products. To the best of our knowledge, the aforementioned drivers and barriers have not yet been studied together.

Conceptual model of the study

As smart products have new capacities due to sensor, network and computing technology, they can be considered innovations. Rogers defines an innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers, 2003, p. 12). Therefore, consumers could perceive smart products as something novel and different in comparison to conventional products. That is why the innovation decision process, as suggested by Rogers (2003), provides the basic framework for our conceptual model. This stepwise approach explains the way the status of consumer adoption evolves over time. A concrete decision about adoption is only made after successful persuasion. This persuasion stage is mainly affected by the perceived characteristics of the innovation, in this case, the smartness characteristics of the product. These characteristics may promote or inhibit adoption (e.g. Henkens *et al.*, 2021; Huang and Hsieh, 2012). By weighing up the promoters and inhibitors, a positive or negative decision leading to either adoption or rejection is ultimately made.

In the past, the technology acceptance model (TAM; Davis, 1989; Venkatesh *et al.*, 2003) has been widely used to investigate and forecast user acceptance based on psychological perceptions. However, according to Kim *et al.* (2007), it has the shortcoming of neglecting perceived value. Therefore, they propose the value-based adoption model (VAM). In their study, they analyze consumer intention to adopt the mobile internet by analyzing the benefits derived from and sacrifices required by the emerging technologies for a given consumer. The benefit components of perceived value are usefulness and enjoyment. Usefulness describes the consumer's assessment of the product performing the desired task while enjoyment describes the pleasure or joy derived from using the technology. In contrast, Kim *et al.* (2007) presume the technicality of mobile internet as well as the perceived fee to be the sacrifice components of perceived value. Technicality is defined as "the degree to which mobile internet is perceived as being technically excellent in the process of providing services" (Kim *et al.*, 2007, p. 116). The perceived fee is the monetary sacrifice consumers must make to use mobile internet. The advantage of the VAM is that it simultaneously considers the benefits and the costs of technology acceptance. The VAM has been validated in various contexts, such as mobile banking (Luo *et al.*, 2010; Zhou, 2013), smartphone applications (Hanafizadeh *et al.*, 2014) and digital artifacts (Turel *et al.*, 2010).

To exploit the full potential of the value components, the use of smart products is inevitably accompanied by a certain release of personal information due to the built-in sensor, network and computing technology. This (unwilling) disclosure of personal data constitutes one potential sacrifice required by smart products, leading to a so-called "privacy calculus" (Li, 2012). According to this theory, individuals are willing to accept the invasion of privacy that comes with smart product use, provided that the benefits (values) derived from disclosing personal information outweigh any potential negative consequences (Culnan and Bies, 2003). Intrusiveness appears to be a major risk factor for adoption (Gutierrez *et al.*, 2019).

Based on the above remarks, a theoretical-conceptual frame of reference is chosen for this study. The VAM provides a suitable framework within which to explain the consumers' perceptions of product intelligence and intentions to use smart products. The drivers identified in the literature (enjoyment and usefulness) match and thus represent the benefit components of the VAM, while the barriers (intrusiveness and control) express the sacrifice component.

Hypothesis development

As mentioned above, the perceptions of potential early-stage users determine whether an innovation will be adopted (Rogers, 2003). How the intelligence of a smart product is perceived contributes to consumers' perceptions of the associated benefits and sacrifices, consequently increasing or reducing adoption intention. The perceived value of material objects such as smart products can be classified as either hedonic or utilitarian (Babin *et al.*, 1994). Following Kim *et al.* (2007), we propose hedonic and utilitarian value in the form of enjoyment and usefulness as the benefit components influencing usage intention.

Smart products entertain consumers as their smartness offers value beyond functionality and performing practical tasks. Venkatesh defines perceived enjoyment as the extent to which "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000, p. 351). In consumer behavior research hedonic motives have been found to be a key predictor of usage behavior (Hirschman and Holbrook, 1982; on smart products, Pal *et al.*, 2020; Yang *et al.*, 2016). Therefore, this study suggests positive mediating effects on the part of the smartness characteristics on adoption intention stemming from an increase in consumers' perceived enjoyment.

Firstly, as smart products operate independently without further activity on the part of consumers (Hoffman and Novak, 2015), they are presumed to have higher levels of *actuation*, allowing the consumer to fully concentrate on enjoyment. Thus, it can be presumed that actuation positively influences usage intention via enjoyment. *Dynamism* enables smart products to learn from their users' behaviors and enhance their functionalities to offer a more satisfactory user experience (Henkens *et al.*, 2021; Weinberg *et al.*, 2015). Therefore, the ability of smart products to adapt and self-improve allows for better entertainment which enhances usage intention. Smart products are aware of and able to react automatically to changes in their environment. Because of this *awareness* (Hoffman and Novak, 2015), consumers do not have to actively engage with aware products, while simultaneously being offered better entertainment value (Foehr and Germelmann, 2020). Thus, the enhanced enjoyment caused by the awareness constitutes an adoption driver. If a smart product exhibits a high degree of *connectivity*, it works together with other entities to achieve a common objective (Henkens *et al.*, 2021; Rijsdijk and Hultink, 2009). This enables an extended range of functions as well as the integration of other beneficial products for a service ecosystem. Therefore, the more the product can collaborate with other products, the more consumers can enjoy them.

The theory of anthropomorphism suggests that humans have a natural tendency to attribute humanlike characteristics, intentions and emotions to non-human entities, including animals, objects and natural phenomena (Guthrie, 1993). The quintessence of prior research is that anthropomorphized objects are treated similarly to human agents (see, e.g. Kim and McGill, 2011; Touré-Tillery and McGill, 2015). If products are capable of *humanlike interaction*, consumers are even more likely to anthropomorphize them. In the smart products currently on the market, humanlike interaction predominantly manifests in the form of voice activation. Kowalczuk (2018) finds that the more the interaction is humanlike, the more consumers enjoy them. For example, the more consumers can control other products in their smart home via their smart speaker in a humanlike manner, the more entertained they are, leading to higher usage intention. We hypothesize as follows:

H1a–e. Perceived (a) actuation, (b) dynamism, (c) awareness, (d) connectivity and (e) humanlike interaction positively affect usage intention mediated by an increase in enjoyment perception.

In this study, usefulness refers to the utilitarian benefit of using smart products. A product or service is considered useful based on two premises: Using it saves the consumer time and relieves the consumer cognitively, emotionally, or physically (Berry *et al.*, 2002). Usefulness has been identified as the strongest predictor of behavioral intention (e.g. De Kerviler *et al.*, 2016; Kim *et al.*, 2007; Venkatesh *et al.*, 2003; Yoon and Kim, 2007). Smart products relieve consumers of effort due to their intelligence, as manifested in their smartness characteristics. Thus, positive mediating effects on the part of the smartness characteristics on adoption intention stemming from an increase in consumers' perceived usefulness are suspected.

If a technology is considered to have high levels of *actuation*, its autonomy saves time as well as effort and facilitates everyday life (Smith *et al.*, 2023; Weinberg *et al.*, 2015). It can therefore be assumed that actuation positively influences usage intention via usefulness. Furthermore, self-improving products, which are considered to have high *dynamism*, can be superior in terms of supporting their users' lives, which, in turn, fosters usage intention (Henkens *et al.*, 2021). Exhibiting high levels of *awareness*, allows consumers to not have to actively engage with these products. Thus, they are relieved of effort, which then increases usage intention (Hoffman and Novak, 2015). Moreover, if smart products work together in a service ecosystem and towards a common goal, consumers experience improved use due to effort facilitation as well as additional and improved functionality (Oyedele and Goenner, 2021). Therefore, perceived *connectivity* fosters usage intention, mediated by usefulness. Lastly, if the *interaction* with the smart product is *humanlike*, consumers' usage intention is enhanced, as they perceive it to be more useful than other products (Kowalczuk, 2018). Similarly, Foehr and Germelmann (2020) find that technologies operated by voice assistants offer usefulness by simplifying everyday life as people can, for instance, interact with their smart speaker without moving, solely by speaking.

The following hypotheses are proposed:

H2a–e. Perceived (a) actuation, (b) dynamism, (c) awareness, (d) connectivity and (e) humanlike interaction positively affect usage intention mediated by an increase in usefulness perception.

However, the benefits considered are also countered by potential sacrifices. In particular, the perception of intrusion is considered to be an inhibiting factor for the adoption of smart products (Mani and Chouk, 2017; Lucia-Palacios and Pérez-López, 2023). Therefore, negative mediation effects on the part of smartness characteristics on adoption intention are hypothesized resulting from a consumer's perceived intrusiveness. The smart products' ability to act autonomously, without the explicit permission of consumers, may elicit feelings of intrusiveness (Hoffman and Novak, 2015; Mani and Chouk, 2017, 2018). Thus, *actuation* lowers usage intention via an increase in intrusiveness (Lucia-Palacios and Pérez-López, 2021). Products that learn from users' behavior by collecting and analyzing data and, perhaps, also a lack of clarity on when and what data are being stored (Mani and Chouk, 2018), may evoke feelings that such products are intrusive. *Dynamism* thus increases the perception of intrusiveness, which, in turn, reduces usage intention. *Awareness* refers to smart products observing their surroundings as well as their users (Henkens *et al.*, 2021). This smartness characteristic in particular evokes the feeling of an invasion of privacy (Edwards *et al.*, 2002; Mani and Chouk, 2017) on the part of the smart product observing its environment with sensors. In line with the privacy calculus, this constitutes a major risk factor, negatively affecting adoption.

While the smartness characteristics mentioned above refer to autonomous action, learning and sensing in the consumer's environment, *connectivity* has a more outward focus in that the smart products can cooperate with other (external) entities. Thus, this ability to cooperate should negatively affect adoption intention due to increased intrusiveness perception. Lastly, people tend to anthropomorphize products (Epley *et al.*, 2007), even more so when they are capable of *humanlike interaction*. If a smart product is assessed as capable of humanlike interaction, people may feel as if the product is listening to them (Uysal *et al.*, 2022). This leads us to believe that having a humanlike smart product feels like an intrusion into people's lives, consequently lowering usage intention. Thus, we hypothesize as follows:

H3a–e. Perceived (a) actuation, (b) dynamism, (c) awareness, (d) connectivity and (e) humanlike interaction negatively affect usage intention mediated by an increase in intrusiveness perception.

Product intelligence also affects consumers' perception of control (Schweitzer and Van den Hende, 2016). People's behavior is strongly influenced by (their confidence in) their ability to maintain control (Ajzen, 1991). People need to feel that they are in control, otherwise, they may feel restricted, which impairs behavioral intention (Brehm, 1966; Faraji-Rad *et al.*, 2017). A recent study by Smith *et al.* (2023) emphasizes how the automation of products, which is a key characteristic of smart products, decreases feelings of control. Schweitzer and Van den Hende (2016) find that product autonomy increases disempowerment, meaning that individuals feel as if they can exert control, which reduces adoption intention. In line with their findings, we assume that *actuation* lowers usage intention via a decrease in control. The more the smart product learns and improves itself, the more consumers feel they are not in control over the product. Thus, *dynamism* decreases the feeling of control, resulting in a negative impact on usage intention (Hoffman and Novak, 2015). Additionally, awareness refers to the automated response of smart products to their environment.

In a similar vein as actuation, we believe that *awareness* impairs perceived control, further inhibiting adoption (Tassiello *et al.*, 2021). We expect negative impacts of *connectivity* via control, as the more a product is connected, the more complex and hard to control it is perceived to be. If a product exhibits high levels of *humanlike interaction* people may feel as if another "person" is making a decision for them, as consumers tend to anthropomorphize them. Schweitzer *et al.* (2019) find that if users feel they are unable to control their voice-controlled smart devices, usage intention is impaired. Therefore, we assume that humanlike interaction lowers usage intentions due to a decrease in control. Thus, the following hypotheses are proposed:

H4a-e. Perceived (a) actuation, (b) dynamism, (c) awareness, (d) connectivity and (e) humanlike interaction negatively affect usage intention mediated by a decrease in control perception.

Figure 1 depicts the conceptual model, showing that product smartness impacts consumers' perceptions of enjoyment, usefulness, intrusiveness and control, which subsequently influence usage intention of smart products.

Survey design, data collection and measure

A scenario-based online study was conducted to test the hypotheses. Surveys were collected by a leading online-panel provider in Germany. The criteria used to ensure the sample's representativeness of the German population were age (18–65 years), gender and region of residence (federal state). People were invited to participate on a continuous basis within a time

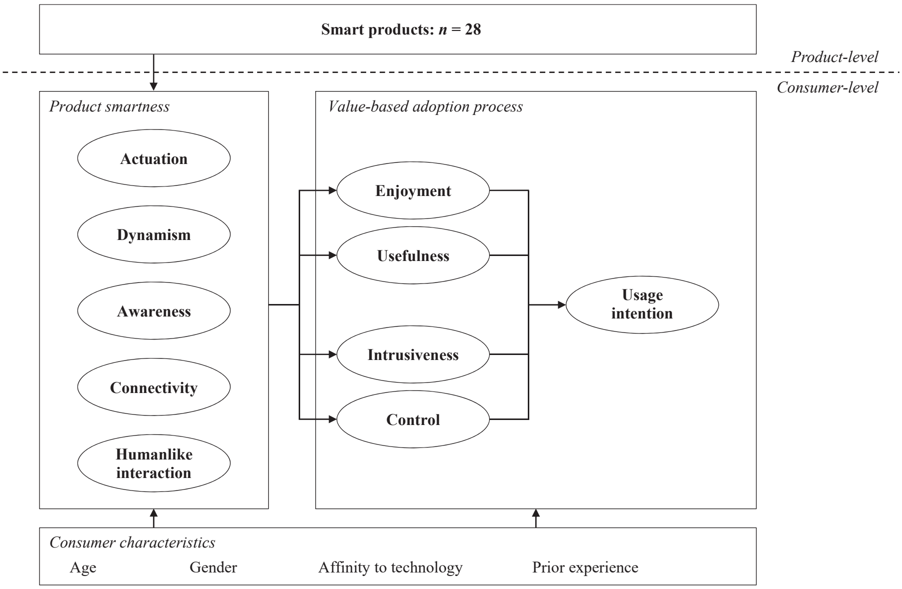

Figure 1.
Conceptual model

Source(s): Figure created by the authors

frame of 2 weeks. Because rolling enrollment was used to obtain a quota sample, calculating nonresponse bias was not possible. In total, 1,170 respondents filled out the survey and received a monetary incentive of € 0.55 for participation. The average response time was 13 min and 48 s. The average age of the respondents was 44.4 years (SD = 14.3) and 52.1% were women.

After answering introductory questions about socio-demographics (age and gender), ensuring the representativeness of the sample and general interest in technology, the participants were randomly assigned (between-subjects design) to one of 28 smart product descriptions. The examined products were selected after extensive desk research and chosen from the smart home context (Borgia, 2014). These products ranged from a smart toothbrush and a smart speaker to a smart washing machine. Short and standardized product descriptions were given to ensure that the respondents had the same idea about the selected smart products and their functions (see Table 4). The respondents were asked to evaluate the randomly assigned product as follows: First, respondents were asked to indicate their intention to use the displayed smart product in the future (adapted from Lamberton and Rose, 2012; Zeithaml *et al.*, 1996). Second, the respondents evaluated the perceived enjoyment and usefulness of the product (Claudy *et al.*, 2015; Franke and Schreier, 2010; Lin *et al.*, 2015) and its intrusiveness (Mani and Chouk, 2017) as well as the perceived control (adapted from Ajzen, 1991). Third, the respondents were asked to rate the product in terms of the five smartness facets. All items are measured on 5-point Likert-type scales, with anchors of 1 ("totally disagree") and 5 ("totally agree").

We used a quality index provided by the survey tool that compares the individual processing time of a respondent with the average duration of the entire sample. All respondents below the value of 0.1 (scaled 0.0–1.0). Further, attention checks in the form of instructed-response items were used.

This study uses multilevel structural equation modeling to test the relationships outlined in the conceptual model, accounting for the variability associated with each level of hierarchy. The consumer-level data (N = 1,170) are nested in 28 groups (i.e. products), resulting in an average

Introduction
In the following we present a so-called smart product. This is a [. . .]. This product contains all the functions of the conventional equivalent. "Smart" about this [. . .] however, are for example the following functions
Product 1: window (M_{AC} = 3.33, SD_{AC} = 1.15; M_{DY} = 3.00, SD_{DY} = 1.00; M_{AW} = 3.55, SD_{AW} = 0.99; M_{CO} = 4.02, SD_{CO} = 0.91; M_{HU} = 2.06, SD_{HU} = 0.87) • The window is connected • The window can be controlled and monitored via app • The window tones itself depending on the brightness • There is a link, for example, with the central heating: window open, heating off
Product 2: washing machine (M_{AC} = 3.31, SD_{AC} = 1.10; M_{DY} = 3.09, SD_{DY} = 1.04; M_{AW} = 2.76, SD_{AW} = 1.03; M_{CO} = 3.56, SD_{CO} = 1.15; M_{HU} = 2.09, SD_{HU} = 1.07) • The washing machine is connected • The washing machine recognizes its contents • Automatic detergent selection and dosing take place • The washing machine can be controlled and monitored via app
Product 3: locking system (M_{AC} = 3.17, SD_{AC} = 1.10; M_{DY} = 3.02, SD_{DY} = 1.10; M_{AW} = 3.52, SD_{AW} = 1.03; M_{CO} = 4.04, SD_{CO} = 0.83; M_{HU} = 2.05, SD_{HU} = 1.10) • The locking system is connected • The locking system can be controlled and monitored via app • For example, the front door recognizes the approach of the smartphone or the faces of the residents and opens automatically
Product 4: smart TV (M_{AC} = 2.67, SD_{AC} = 1.09; M_{DY} = 3.17, SD_{DY} = 0.90; M_{AW} = 2.90, SD_{AW} = 1.12; M_{CO} = 3.91, SD_{CO} = 0.99; M_{HU} = 2.26, SD_{HU} = 1.03) • The smart TV is connected • The smart TV can play video and audio files • It has voice recognition and control • Assistants such as Alexa, Siri, etc. can be used
Product 5: smart speaker (M_{AC} = 2.90, SD_{AC} = 1.06; M_{DY} = 3.52, SD_{DY} = 1.00; M_{AW} = 3.47, SD_{AW} = 1.00; M_{CO} = 4.00, SD_{CO} = 0.81; M_{HU} = 2.79, SD_{HU} = 1.07) • The smart speaker is connected • The smart speaker can play audio files • It has voice recognition and control • Assistants such as ALexa, Siri, etc. Can be used • Other smart devices can be controlled with the smart speaker
Product 6: robot animal (M_{AC} = 3.06, SD_{AC} = 0.90; M_{DY} = 3.44, SD_{DY} = 0.90; M_{AW} = 3.52, SD_{AW} = 0.89; M_{CO} = 4.02, SD_{CO} = 0.69; M_{HU} = 2.53, SD_{HU} = 0.96) • The robot animal is connected • It has voice recognition and control • The robot animal can interact with other smart products
Product 7: food processor (M_{AC} = 3.10, SD_{AC} = 1.12; M_{DY} = 2.75, SD_{DY} = 0.99; M_{AW} = 2.02, SD_{AW} = 0.97; M_{CO} = 3.34, SD_{CO} = 1.08; M_{HU} = 2.14, SD_{HU} = 0.91) • The food processor is connected • The food processor displays recipes and step by step instructions from the Internet • The food processor performs automatic preparation of dishes
Product 8: running shoe (M_{AC} = 3.16, SD_{AC} = 1.03; M_{DY} = 3.04, SD_{DY} = 0.92; M_{AW} = 2.71, SD_{AW} = 1.03; M_{CO} = 3.95, SD_{CO} = 0.99; M_{HU} = 2.02, SD_{HU} = 0.84) • The running shoe is connected • The running shoe has GPS • The running shoe measures, e.g. running speed, rolling behavior, joint stability • The wear of the running shoe can be monitored with an app • The running behavior can be analyzed via app

(*continued*)

Table 4.
Description of product framing

Introduction
Product 9: toothbrush (M_{AC} = 2.80, SD_{AC} = 1.09; M_{DY} = 3.00, SD_{DY} = 1.21; M_{AW} = 2.80, SD_{AW} = 1.09; M_{CO} = 3.74, SD_{CO} = 0.94; M_{HU} = 1.97, SD_{HU} = 1.07) • The toothbrush is connected • The toothbrush monitors brushing time and pressure applied • The toothbrush enables health monitoring: monitoring and analysis of brushing behavior and teeth through networking with app
Product 10: pajama (M_{AC} = 2.94, SD_{AC} = 1.04; M_{DY} = 2.72, SD_{DY} = 1.06; M_{AW} = 2.64, SD_{AW} = 1.12; M_{CO} = 3.48, SD_{CO} = 0.96; M_{HU} = 1.75, SD_{HU} = 0.84) • The pajama is connected • The pajama enables health monitoring: monitoring and analysis of sleep behavior and body functions through networking with app
Product 11: refrigerator (M_{AC} = 3.43, SD_{AC} = 1.08; M_{DY} = 3.09, SD_{DY} = 1.12; M_{AW} = 3.10, SD_{AW} = 1.28; M_{CO} = 3.71, SD_{CO} = 1.00; M_{HU} = 2.23, SD_{HU} = 1.23) • The refrigerator is connected • The refrigerator can be controlled and monitored via app (e.g. real-time images of the contents) • The refrigerator has automatic order triggering • The refrigerator can make recipe suggestions based on the contents
Product 12: baby monitor (M_{AC} = 3.45, SD_{AC} = 0.77; M_{DY} = 2.81, SD_{DY} = 0.98; M_{AW} = 3.79, SD_{AW} = 0.86; M_{CO} = 4.10, SD_{CO} = 0.75; M_{HU} = 2.26, SD_{HU} = 1.00) • The baby monitor is connected • When the baby is active (crying, awakening, etc.), the app notifies • The baby monitor shows real-time images via app
Product 13: fitness tracker (M_{AC} = 3.23, SD_{AC} = 0.82; M_{DY} = 2.96, SD_{DY} = 0.93; M_{AW} = 3.09, SD_{AW} = 0.85; M_{CO} = 3.79, SD_{CO} = 0.87; M_{HU} = 2.05, SD_{HU} = 1.05) • The fitness tracker is connected • The fitness tracker has GPS • The fitness tracker enables health monitoring: monitoring and analysis of body data through networking with app
Product 14: robotic lawnmower (M_{AC} = 4.05, SD_{AC} = 0.71; M_{DY} = 3.48, SD_{DY} = 1.11; M_{AW} = 3.94, SD_{AW} = 0.85; M_{CO} = 3.68, SD_{CO} = 0.96; M_{HU} = 2.58, SD_{HU} = 1.35) • The robotic lawnmower is connected • The robotic lawnmower can mow independently • The robotic lawnmower recognizes its surroundings (space and ground) • The robotic lawnmower can be controlled and monitored via app
Product 15: robotic vacuum cleaner (M_{AC} = 3.96, SD_{AC} = 0.82; M_{DY} = 3.47, SD_{DY} = 1.07; M_{AW} = 3.81, SD_{AW} = 0.88; M_{CO} = 3.50, SD_{CO} = 0.97; M_{HU} = 1.98, SD_{HU} = 1.08) • The robotic vacuum cleaner is connected • The robotic vacuum cleaner can vacuum independently • The robotic vacuum cleaner recognizes its surroundings (room and surface) • The robotic vacuum cleaner can be controlled and monitored via app
Product 16: toilet (M_{AC} = 3.40, SD_{AC} = 0.84; M_{DY} = 3.07, SD_{DY} = 1.02; M_{AW} = 3.63, SD_{AW} = 0.94; M_{CO} = 3.76, SD_{CO} = 0.88; M_{HU} = 1.94, SD_{HU} = 0.91) • The toilet is connected • The seat heats up depending on the environment • The toilet enables health monitoring: monitoring and analysis of body data and excretions by networking with an app
Product 17: smartphone (M_{AC} = 2.82, SD_{AC} = 0.92; M_{DY} = 3.25, SD_{DY} = 1.04; M_{AW} = 3.52, SD_{AW} = 0.90; M_{CO} = 4.06, SD_{CO} = 0.82; M_{HU} = 2.48, SD_{HU} = 0.96) • The smartphone is connected • The smartphone has facial recognition • The smartphone has GPS. • It has voice recognition and control • Assistants such as Alexa, Siri, etc. can be used

(*continued*)

Table 4.

Introduction
Product 18: drone (M_{AC} = 2.54, SD_{AC} = 1.09; M_{DY} = 2.51, SD_{DY} = 1.03; M_{AW} = 3.34, SD_{AW} = 0.93; M_{CO} = 4.08, SD_{CO} = 0.87; M_{HU} = 1.78, SD_{HU} = 1.01)
• The drone is connected • The drone has GPS • The drone enables image and video recording • The drone can be controlled by connecting to mobile devices (smartphone or smart controller)
Product 19: lighting system (M_{AC} = 3.38, SD_{AC} = 0.95; M_{DY} = 3.62, SD_{DY} = 0.96; M_{AW} = 3.52, SD_{AW} = 1.02; M_{CO} = 3.71, SD_{CO} = 0.80; M_{HU} = 2.10, SD_{HU} = 1.01)
• The lighting system is connected • The lighting system can be controlled and monitored via app • The lighting system automatically adapts to the environment • The lighting system learns from habits
Product 20: heating system (M_{AC} = 3.63, SD_{AC} = 0.83; M_{DY} = 3.96, SD_{DY} = 0.74; M_{AW} = 4.05, SD_{AW} = 0.74; M_{CO} = 3.87, SD_{CO} = 0.85; M_{HU} = 2.29, SD_{HU} = 0.85)
• The heating system is connected • The heating system can be controlled and monitored via app • The heating system automatically adapts to the environment • There is a link with the windows, for example: windows open, heating off • The heating system learns from habits
Product 21: mirror (M_{AC} = 3.06, SD_{AC} = 1.07; M_{DY} = 3.12, SD_{DY} = 0.99; M_{AW} = 3.57, SD_{AW} = 0.98; M_{CO} = 3.83, SD_{CO} = 0.71; M_{HU} = 2.15, SD_{HU} = 0.87)
• The mirror is connected • The mirror can play audio and video files • It optimizes the lighting depending on the environment • The mirror gives real-time weather conditions and forecasts • It gives outfit suggestions according to weather (forecast) and appointments (by linking with smartphone)
Product 22: smart watch (M_{AC} = 3.36, SD_{AC} = 0.87; M_{DY} = 3.32, SD_{DY} = 1.03; M_{AW} = 3.30, SD_{AW} = 1.12; M_{CO} = 4.12, SD_{CO} = 1.01; M_{HU} = 2.22, SD_{HU} = 1.06)
• The smart watch is connected • The smart watch has GPS • The smart watch measures various body functions • By networking with the smartphone, phone calls can be made and there is Internet access
Product 23: game console (M_{AC} = 3.20, SD_{AC} = 0.90; M_{DY} = 3.31, SD_{DY} = 0.89; M_{AW} = 3.38, SD_{AW} = 0.96; M_{CO} = 4.02, SD_{CO} = 0.87; M_{HU} = 2.47, SD_{HU} = 1.19)
• The game console is connected • The game console enables sharing via social networks • The game console allows you to play against other players online • The game console can analyze gaming behavior
Product 24: watering system (M_{AC} = 3.62, SD_{AC} = 1.07; M_{DY} = 3.00, SD_{DY} = 1.20; M_{AW} = 3.88, SD_{AW} = 0.89; M_{CO} = 3.62, SD_{CO} = 1.03; M_{HU} = 2.21, SD_{HU} = 1.06)
• The watering system is connected • The watering system enables independent watering of the garden or house plants • The watering system detects its environment (moisture of the soil, evaporation, etc.) • The watering system can be controlled and monitored via app
Product 25: body scale (M_{AC} = 3.03, SD_{AC} = 1.17; M_{DY} = 3.18, SD_{DY} = 0.96; M_{AW} = 2.74, SD_{AW} = 1.23; M_{CO} = 3.96, SD_{CO} = 0.90; M_{HU} = 2.55, SD_{HU} = 1.27)
• The body scale is connected • The body scale enables health monitoring: monitoring and analysis of body data through networking with app

(*continued*)

Table 4.

Introduction
Product 26: baby crib (M_{AC} = 3.28, SD_{AC} = 0.93; M_{DY} = 2.97, SD_{DY} = 1.09; M_{AW} = 3.19, SD_{AW} = 1.02; M_{CO} = 3.81, SD_{CO} = 0.89; M_{HU} = 2.43, SD_{HU} = 1.08) • The baby crib is connected • The baby crib enables health monitoring of the baby: monitoring and analysis of body data through networking with app
Product 27: clinical thermometer (M_{AC} = 3.30, SD_{AC} = 1.10; M_{DY} = 2.85, SD_{DY} = 1.25; M_{AW} = 2.42, SD_{AW} = 1.19; M_{CO} = 3.71, SD_{CO} = 0.86; M_{HU} = 2.45, SD_{HU} = 1.15) • The clinical thermometer is connected • The clinical thermometer enables health monitoring: monitoring and analysis of body data through networking with app
Product 28: care robot (M_{AC} = 3.27, SD_{AC} = 1.02; M_{DY} = 3.37, SD_{DY} = 1.13; M_{AW} = 3.62, SD_{AW} = 1.00; M_{CO} = 3.67, SD_{CO} = 0.93; M_{HU} = 2.69, SD_{HU} = 1.08) • The care robot is connected • The care robot has voice recognition and control • The care robot takes over pick-up and drop-off services • In emergency situations, e.g. in the event of a fall, the robot establishes a video connection to an emergency center. In this way, communication can take place via the robot and appropriate measures can be initiated • The care robot makes it possible to communicate with the user from outside the home or to look in on the user's home

Note(s): M = mean, *SD* = standard deviation, AC = Actuation, DY = Dynamism
AW = Awareness, CO = Connectivity and HU = Humanlike interaction
Source(s): Table created by the authors

Table 4.

cluster size of 42 Notably, the group-level sample size (28 products) is higher than the minimum sample size of 20 typically suggested in the literature (e.g. Preacher *et al.*, 2011). A further basic premise of multilevel modeling is that there is sufficient variation between the groups being observed observations. Intraclass correlations (ICCs) can serve as indicators because they measure the degree of similarity within the same cluster and are recommended to be greater than 0.05 (Preacher *et al.*, 2010). The ICCs calculated for the dependent variables are substantial for the majority of the examined variables: actuation (0.10), usage intention (0.09), enjoyment (0.07), usefulness (0.07) and dynamism (0.07). However, between-category variance is limited for intrusiveness (0.04), control (0.01), awareness (0.03), connectivity (0.02) and humanlike interaction (0.03). In sum, the ICCs are sufficient to justify the use of multilevel modeling. We examine the measurement reliability of the reflective constructs through multilevel confirmatory factor analysis using Mplus 7.4 (Muthén and Muthén, 2015). Table 5 shows the results. The global fit indices (see notes of Table 5) indicate a very good model fit, as comparative fit index (CFI) and Tucker–Lewis index (TLI) both exceed the recommended threshold of 0.9, while root mean square error of approximation (RMSEA) and standardized root mean squared residual (SRMR) are below 0.05 (Hu and Bentler, 1999).

Cronbach's alpha is well above the required level of 0.7 for all constructs. The composite reliabilities of the reflective constructs exceed 0.7, the recommended threshold (Bagozzi and Yi, 1988). Moreover, the findings show discriminant validity between the constructs, as none of the squared correlation coefficients between any of the constructs exceed the average variance extracted for a construct (Fornell and Larcker, 1981; correlations in Table 6).

Results

The results (presented in Tables 7 and 8) show that both benefit facets are significantly and positively related to usage intention (enjoyment: ß = 0.431, $p < 0.001$; usefulness: ß = 0.316, $p < 0.001$). Intrusiveness is significantly and negatively related to usage intention (ß = −0.057, $p = 0.034$), while the effect control on usage intention is not significant (ß = 0.029, $p = 0.371$).

Construct	Factor Loading	Composite reliability	Average variance extracted
Usage intention (adapted from Lamberton and Rose, 2012; Zeithaml *et al.*, 1996)		0.940	0.839
If I needed a smart product, I would use the presented product	0.851		
I can see myself using this product in the future	0.955		
It is likely that I will use this product in the future	0.939		
Enjoyment (adapted from Franke and Schreier, 2010)		0.940	0.840
I have pleasure from this product	0.936		
I think this product is very enjoyable	0.926		
This product is fun to use	0.886		
Usefulness (Claudy *et al.*, 2015; Lin *et al.*, 2015)		0.926	0.808
This product supports me	0.893		
This product makes my everyday life easier	0.897		
This product is convenient	0.906		
Intrusiveness (Mani and Chouk, 2017)		0.932	0.732
The product is intrusive	0.871		
The product is irritating	0.859		
The product is indiscreet	0.828		
I am not comfortable with the product	0.875		
The product is disturbing	0.845		
Control (adapted from Ajzen, 1991)		0.896	0.742
I feel like I am in control when I use this product	0.922		
With this product, the customer has the "say"	0.828		
Using this product gives me a sense of control	0.831		
Smartness characteristics (Henkens *et al.*, 2021; Rijsdijk and Hultink, 2009)			
Actuation		0.818	0.601
This product takes the initiative	0.827		
This product works independently	0.675		
This product does things by itself	0.815		
Dynamism		0.874	0.699
This product can learn	0.843		
This product improves itself	0.847		
This product delivers a better performance over time	0.817		
Awareness		0.851	0.656
This product keeps an eye on its environment	0.841		
This product directly adapts its behavior to the environment	0.821		
This product observes its environment	0.765		
Connectivity		0.838	0.633
This product communicates with other devices	0.847		
This product achieves a common goal in cooperation with other products	0.733		
This product can be attached to other products	0.803		
Humanlike Interaction		0.897	0.743
This product is capable of communicating and interacting with the user in a natural, human way	0.833		
Communication with this product is humanlike	0.897		
Interaction with this product is humanlike	0.855		

Note(s): Global fit indices: CFI 0.975; TLI 0.970; RMSEA 0.028; SRMR 0.042
Source(s): Table created by the authors

Table 5. Measurement of latent constructs and results of confirmatory factor analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Usage intention	1									
(2) Enjoyment	0.800	1								
(3) Usefulness	0.775	0.838	1							
(4) Intrusiveness	−0.596	−0.633	−0.625	1						
(5) Control	0.643	0.706	0.688	−0.623	1					
(6) Actuation	0.221	0.298	0.354	−0.172	0.255	1				
(7) Dynamism	0.359	0.401	0.410	−0.219	0.354	0.484	1			
(8) Awareness	0.206	0.230	0.263	−0.053	0.172	0.413	0.468	1		
(9) Connectivity	0.259	0.277	0.282	−0.152	0.237	0.277	0.335	0.392	1	
(10) Humanlike interaction	0.398	0.422	0.413	−0.257	0.412	0.318	0.489	0.322	0.237	1

Source(s): Table created by the authors

Table 6.
Correlations

	Std. Coefficient	R^2
Dependent variable: usage intention		74.2%
Enjoyment (+)	0.431***	
Usefulness (+)	0.316***	
Intrusiveness (–)	−0.057**	
Control (+)	0.029	
Smartness characteristics		
Actuation	−0.082***	
Dynamism	0.005 n.s	
Awareness	0.019 n.s	
Connectivity	0.008 n.s	
Humanlike interaction	0.048*	
Dependent variable: enjoyment		46.8%
Actuation	0.089***	
Dynamism	0.144***	
Awareness	−0.113***	
Connectivity	0.093***	
Humanlike interaction	0.300***	
Dependent variable: usefulness		44.5%
Actuation	0.134***	
Dynamism	0.124***	
Awareness	−0.107***	
Connectivity	0.142***	
Humanlike interaction	0.295***	
Dependent variable: intrusiveness		25.4%
Actuation	−0.042 n.s	
Dynamism	*−0.081*	
Awareness	0.197***	
Connectivity	−0.089***	
Humanlike interaction	−0.224***	
Dependent variable: control		35.1%
Actuation	0.033 n.s	
Dynamism	0.148***	
Awareness	−0.135***	
Connectivity	0.083**	
Humanlike interaction	−0.340***	

Note(s): N = 1,170; Significant results (two-tailed) at $p < 0.01$ (***) and $p < 0.05$ (**) are in underline, results ($p < 0.10$, *) are in italics and nonsignificant effects (n.s.) are in normal font
Source(s): Table created by the authors

Table 7.
Assessment of direct effects on consumer level

Mediation paths	ß (std.)	SE	95%-CI (std) Interval low	Interval high
Dependent variable: usage intention				
Actuation via enjoyment	0.037**	0.015	0.007	0.066
Actuation via usefulness	0.042***	0.013	0.016	0.069
Actuation via intrusiveness	0.002	0.003	−0.003	0.007
Actuation via control	−0.001	0.002	−0.002	0.004
Dynamism via enjoyment	0.060***	0.017	0.025	0.094
Dynamism via usefulness	0.039***	0.014	0.012	0.067
Dynamism via intrusiveness	0.005	0.003	−0.002	0.001
Dynamism via control	−0.004	0.005	−0.005	0.014
Awareness via enjoyment	−0.047***	0.016	−0.077	−0.016
Awareness via usefulness	−0.034***	0.013	−0.059	−0.009
Awareness via intrusiveness	*−0.011**	0.003	−0.023	−0.000
Awareness via control	0.004	0.003	−0.013	0.005
Connectivity via enjoyment	0.039***	0.013	0.013	0.064
Connectivity via usefulness	0.045***	0.012	0.021	0.068
Connectivity via intrusiveness	0.005	0.003	−0.001	0.001
Connectivity via control	−0.002	0.003	−0.003	0.008
Humanlike interaction via enjoyment	0.124***	0.020	0.084	0.164
Humanlike interaction via usefulness	0.093***	0.018	0.058	0.129
Humanlike interaction via intrusiveness	0.013	0.006	0.000	0.025
Humanlike interaction via control	−0.010	0.011	−0.012	0.032

Note(s): Global fit indices: CFI 0.968; TLI 0.962; RMSEA 0.031; SRMR 0.042
$N = 1{,}170$; significance according to confidence intervals determined in *RMediation*; significant results at $p < 0.01$ (***) and $p < 0.05$ (**) are in underline, results $p < 0.10$ (*) are in italics and nonsignificant effects (n.s.) are in normal font
Source(s): Table created by the authors

Table 8. Assessment of indirect effects on consumer-level

The effect of actuation on usage intention is positively mediated by enjoyment ($B = 0.037$, $SE = 0.015$, CI_{95}: 0.007 to 0.066) and usefulness ($B = 0.042$, $SE = 0.013$, CI_{95}: 0.016 to 0.069), but not significantly mediated by intrusiveness ($B = 0.002$, $SE = 0.003$, CI_{95}: −0.003 to 0.007) or by control ($B = -0.001$, $SE = 0.002$, CI_{95}: −0.002 to 0.004). These results provide support for H1a and H2a, but not H3a or H4a. The positive mediated effects are counter-balanced by a significant and negative direct effect on the part of actuation on usage intention (ß = −0.082, $p = 0.001$), implying competitive mediation (Zhao *et al.*, 2010).

The indirect effects of dynamism via enjoyment ($B = 0.060$, $SE = 0.017$, CI_{95}: 0.025 to 0.094) and usefulness ($B = 0.039$, $SE = 0.014$, CI_{95}: 0.012 to 0.067) are positive and significant, while the direct effect is not significant (ß = 0.005, $p = 0.854$). These results provide support for indirect-only mediation effects proposed by H1b and H2b. The effect of dynamism via intrusiveness ($B = 0.005$, $SE = 0.003$, CI_{95}: −0.002 to 0.001) and control is not significant ($B = -0.004$, $SE = 0.003$, CI_{95}: -0.013 to 0.005), thus, H3b and H4b are not supported.

However, the effect of awareness on usage intention is negatively influenced by enjoyment ($B = -0.047$, $SE = 0.016$, CI_{95}: −0.077 to −0.016) and usefulness ($B = -0.034$, $SE = 0.013$, CI_{95}: −0.059 to −0.009). As these effects are opposite to the hypothesized direction H1c, H2c and H4c are rejected. The effects of awareness on usage intention via intrusiveness ($B = -0.011$, $SE = 0.003$, CI_{95}: −0.023 to 0.000) and control ($B = 0.004$, $SE = 0.003$, CI_{95}: −0.013 to 0.005) are not significant as well; thus, H3c and H4c are also rejected.

Positive indirect effects on usage intention exist for connectivity. Even though there is no significant direct effect (ß = 0.008, $p = 0.704$), significant and positive mediation effects via enjoyment ($B = 0.039$, $SE = 0.013$, CI_{95}: 0.013 to 0.064) and usefulness ($B = 0.045$, $SE = 0.012$,

CI_{95}: 0.021 to 0.068) are found, implying indirect-only mediation. Thus, hypotheses H1d and H2d are supported. In contrast, no significant indirect relationship exists between connectivity and usage intention via intrusiveness ($B = 0.005$, $SE = 0.003$, CI_{95}: −0.001 to 0.001) or control ($B = -0.002$, $SE = 0.003$, CI_{95}: −0.003 to 0.008). Thus, H3d and H4d are rejected.

The effect of humanlike interaction on usage intention is positively mediated by enjoyment ($B = 0.124$, $SE = 0.020$, CI_{95}: 0.084 to 0.164) and usefulness ($B = 0.093$, $SE = 0.018$, CI_{95}: 0.058 to 0.129). However, there is no significant mediation via intrusiveness ($B = 0.013$, $SE = 0.006$, CI_{95}: 0.000 to 0.025) or control ($B = -0.001$, $SE = 0.002$, CI_{95}: −0.012 to 0.032). These results provide support for H1e and H2e, but not H3e or H4e. The positive mediated effects are enhanced by a significant and positive direct effect on the part of humanlike interaction on usage intention ($ß = 0.048$, $p = 0.048$), implying complementary mediation (Zhao *et al.*, 2010).

Discussion

Our research sheds light on how product smartness affects usage intention via conflicting mediators. The results of our study show that higher levels of product smartness in the form of actuation, dynamism, connectivity and humanlike interaction are associated with higher levels of enjoyment and usefulness, resulting in higher usage intention. This finding is in line with previous studies (e.g. Henkens *et al.*, 2021; Kaldewei and Stummer, 2018) concluding that product intelligence increases consumer benefit and this positively influences usage intention. All in all, our study advances existing literature on smart products by shining a light on how product intelligence is perceived and has an indirect effect: While prior research has studied product smartness on an aggregate level (e.g. Rijsdijk *et al.*, 2007) or for single facets (e.g. Chouk and Mani, 2022; Schweitzer and Van den Hende, 2016), simultaneous consideration of the influence of the different facets has been largely neglected. Our research enriches these works by considering the contribution of each smartness facet to gain deeper insights into the perceptual differences and how this affects consumers' perceptions and adoption intention, thus also contributing to the literature on product adoption.

Contrary to our expectations, awareness is negatively related to enjoyment and usefulness, thus lowering usage intention. Consumers may not assess smart products being aware as beneficial. Instead, awareness may cause feelings of surveillance activity, preventing consumers from enjoying smart products carelessly and from deriving utility from them. This finding is in accordance with "privacy calculus" (Culnan and Bies, 2003) as the potential data disclosure seems to outweigh the benefits of said disclosure, hence being in line with the phenomenon of the calculus. Furthermore, actuation lowers usage intention directly. This supports Leung *et al.* (2018) findings, which highlight that automation interferes with individuals' attributions to their skill level and feelings of accomplishment, leading to resistance.

Our study aligns with prior research (Jörling *et al.*, 2020; Kowalczuk, 2018), further confirming the importance of humanlike interaction as it is the strongest adoption driver, significantly impacting enjoyment and usefulness. Nevertheless, this is not without caveat: We find that humanlike interaction also strongly negatively relates to perceived control. This finding is in line with Mori *et al.* (2012). Instead of the anticipated positive effects, the human resemblance may trigger feelings of discomfort, known as the "uncanny valley". In consequence, our study contributes to the literature on anthropomorphism by providing empirical evidence of a negative (side) effect that humanlike interaction might cause.

The sacrifices impacted by products' smartness are represented by consumers' perceptions of their intrusiveness and their impact on control. Only the smartness characteristic of awareness increases the perception of intrusiveness marginally, consequently leading to lower usage intentions. These findings are consistent with previous work concluding that intrusiveness negatively impacts consumer acceptance of smart products and services (Mani and Chouk, 2017; Lucia-Palacios and Pérez-López, 2023). As mentioned above, it can be assumed that awareness implies surveillance activity, causing feelings of privacy violations to the consumers. These findings contribute to the literature on innovation resistance and confirm that selected aspects of product intelligence evoke unintended, negative consequences.

However, while previous research finds a significant influence of perceived control on usage intention (e.g. Schweitzer and Van den Hende, 2016), product smartness has no influence on perceived control in the present study and perceived control is unrelated to usage intention. Potentially, the selected smart products do not affect consumers' perceived control. Perceived control can be considered a hygiene factor as it does not contribute directly to technology acceptance, but rather its absence would result in lower technology acceptance. Another explanation may be that consumers in this study do not have a significant desire for control, either as an individual trait or as a situational state; therefore, their willingness to accept smart products is not impinged upon.

Lastly, our research examined various smart products to understand consumer preferences. We find that between-category variance is limited for intrusiveness, control, awareness, connectivity and humanlike interaction, as the ICCs are below the required threshold of 0.05 (see e.g. Preacher *et al.*, 2010). Therefore, the findings regarding these factors hold true regardless of the product category.

All in all, our research proposed and validated a conceptual model based on the VAM of Kim *et al.* (2007). We find that consumers primarily focus on the value benefits that smart products offer and enable and for the most part disregard the negative aspects of smart product usage. Thus, we advance the literature on product adoption by detecting that the positives outweigh the negatives, confirming, e.g. Kowalczuk's (2018) findings.

Implications

The present study has numerous practical implications. Most dimensions of product intelligence lead to enjoyment and contribute to the perception of usefulness. With the exception of awareness, it can be summed up that the smarter the product, the higher the enjoyment or usefulness, in turn, increasing adoption intention. That is why we derive implications for the respective smartness dimensions.

Humanlike interaction is the strongest driver of usage intention, both directly and via enjoyment and usefulness. Products exhibiting comparatively high levels of humanlike interaction in this study are smart speakers (M_{HU} = 2.79) and robots assisting in home care (M_{HU} = 2.69). Enabling humanlike interaction could be achieved by including elements of anthropomorphism, for example by implementing the functionality of operating a product with voice commands. Products such as Amazon's virtual assistant "Alexa" or the gesture control of devices in vehicles (e.g. BMW's 7 Series) can serve as examples. Robotic lawnmowers or vacuum cleaners could be designed with humanlike features and marketed as family companions, e.g. by being referred to with a name (case in point again, Amazon's "Alexa") or being from the same "product family".

Product developers should also enable devices to act autonomously, as it increases usage intention via enhanced enjoyment and usefulness. In this study, smart products such as the robotic lawn mower (M = 4.05) and vacuum cleaner (M = 3.96) are perceived as exhibiting high levels of actuation. Their autonomous functionality fosters usefulness and enjoyment by relieving users of household chores. However, as actuation itself also directly lowers usage intention, product communication should highlight the fun factor and usefulness resulting from the self-employment of smart products. Tesla's "Revolutionize Your Commute" comes to mind as a successful campaign, promoting the benefits of their autopilot. Another measure might be to inform consumers about the autonomous functions and shine a light into the black box of product operations. For example, informative video material about smart products' reasoning processes could lower consumer refusal. Also, allowing consumers to intervene has been identified as a good measure to lower the negative impact of automation (Schweitzer and Van den Hende, 2016). Therefore, product design typically offers the possibility to control, take over, or cancel the product operations, e.g. by monitoring the products' operations and status in a respective app. A prominent example is the iRobot Home App for operating and monitoring the "Roomba" robotic vacuum cleaners.

Products that are perceived as being able to learn and adapt also lead to more enjoyment and usefulness. Dynamism requires AI software (Raff *et al.*, 2020), which is not yet a market standard for the majority of consumer technology. As enhancing dynamism offers the potential to increase the acceptance of smart products, providers should consider advancing smart products in that regard. A successful example are Tesla's vehicles with autonomous driving capabilities: The AI algorithm analyzes environmental data and safely navigates the car within specified areas. Dynamism offers particular potential for providers of smart services, as it offers new opportunities to increase efficiency, provide personalized experiences and adapt their offerings to users' specific needs and preferences. This will increase the acceptance of smart services by making them more fun and useful.

Connectivity also relates positively to enjoyment and usefulness perceptions, increasing usage intention. Successful examples of smart products exhibiting high levels of connectivity are smart home systems such as Google Home. The possibility of linking products together should be considered to make their use as pleasant and useful as possible. This is typically achieved by linking the products with the help of a user ID. Furthermore, marketing communications should highlight the benefits of smart products working together as a (service) ecosystem. For example, Miele promotes their "Miele@home" system by highlighting the convenience and efficiency of connecting their smart products.

Lastly, to avoid the negative effects caused by smart products' awareness, it should be clearly communicated why and what data are being collected, processed and stored and which benefits are enabled by customer data (Malhotra *et al.*, 2004). This can be achieved, for example, via push messages on a corresponding app. That way, consumers are informed about the necessity of data generation (Schumann *et al.*, 2014) and can explicitly give their consent to the use, thus ensuring, that enjoyment and usefulness are not negatively impacted.

Limitations and further research

This research has limitations that suggest avenues for future research. First, the use of text-based manipulations of smart products is rather hypothetical. Especially given that some of the smart products are not yet known (e.g. smart toilet), let alone diffused, evaluation may have been difficult for the subjects due to a lack of prior experience. Furthermore, the product framing may have biased the results regarding connectivity as well as perceived control. Visual exposures could represent stronger and less biased manipulations. Additionally, the consideration of technical components, such as microphones or cameras, could contribute to an explanation. In that case, a clear distinction between input-oriented features (e.g. connectivity) and output-oriented features (e.g. playing audio and video files) is of importance. This distinction will help avoid potential bias and provide a more accurate representation of the relationships between the various aspects of smart products. Further research might also consider using real buying behavior as well as continuous usage behavior, to improve external validity.

Second, this study intends to provide for the generalizability of the conceptual model by including a large variety of smart products and controls for the nested data structure in an appropriate multilevel design. The notable differences in the levels of the smartness characteristics and the adoption drivers and barriers provide a good starting point for further research to shed light on potential causes. However, all examined smart products can be attributed to the extended smart home context. Future research should consider further application contexts such as smart health or smart mobility. Third, there may be differences in subjects as well as cultural differences related to the perception of smart products. Diverging adoption rates in individual countries suggest that the popularity of these products may not depend only on differences between of societies in terms of wealth. Rather cultural factors as well as diverse understandings of privacy protection may also play a role.

Lastly, we excluded smart services from our study due to model complexity. However, as a lot of smart products are embedded in ecosystems differentiating value-based adoption factors of product and service components would be another exciting field of research.

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