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ORIGINAL EMPIRICAL RESEARCH

How product complexity affects consumer adoption of new products: The role of feature heterogeneity and interrelatedness

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Abstract

Recent technological advancements allow companies to incorporate increasingly heterogeneous and interrelated features into their products, which heightens the products' complexity. In four experimental studies conducted with two product categories, this article reveals similarities and differences in terms of how the heterogeneity and interrelatedness of product features influence consumer attitudes (i.e., expected product usability and capability) and, in turn, purchase intentions. Moreover, it shows that both neglected dimensions of product complexity affect the corresponding influence of the number of product features but do so in considerably different ways. The findings suggest that companies can foster consumer adoption by deemphasizing a product's feature heterogeneity, thereby avoiding low expected product usability, and by emphasizing its feature interrelatedness, thereby promoting high expected product capability. This article provides insights into how companies can manage the complexity of products during both product design (i.e., before market launch) and product advertising and selling (i.e., after market launch).

Keywords Product features · Product complexity · Product configuration · Product design · New product development · Consumer adoption · Feature fatigue

To enhance product capability (i.e., ability to perform desired functions) and thus respond to rising consumer needs and competitive pressure, companies have made products such as home control systems, communication devices, and cars increasingly complex by adding more product features (Bettencourt & Bettencourt, 2011; Fürst & Staritz, 2022). In their quest to further improve product capability, companies have taken advantage of recent advancements in manufacturing, electronics, and information technology to implement increasingly heterogeneous and interrelated product features that further increase products' structural complexity (Gubbi et al., 2013; Kannan & Li, 2017). For example, today's smart home systems offer control of not only housing technology (e.g., blinds) but also entertainment (e.g., televisions) and household (e.g., coffee machines) technologies, and their features can be interrelated, such that blinds can be connected with the television and the coffee machine. Yet whether these emerging additional levers for increasing a product's complexity actually enhance consumers' perceived product capability or whether they predominantly reduce consumers' perceived product usability (i.e., ease of learning and using) remains unclear. Because these consumer perceptions are important drivers of consumer adoption of new products, corresponding knowledge is highly managerially relevant (Nysveen et al., 2005; Sääksjärvi & Samiee, 2011).

Despite the importance of knowledge about consumer perceptions of complex products, previous research on product complexity primarily takes a company perspective by analyzing effects of product architecture on internal R&D or manufacturing processes and costs (e.g., Lau et al., 2011; Song et al., 2015) and how best to handle the related complexity, such as through modular product architectures (e.g., Bonvoisin et al., 2016; Campagnolo & Camuffo, 2010). The few exceptions adopting a consumer perspective are limited to a unidimensional conceptualization of product complexity through

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the number of product features (Goodman & Irmak, 2013; Sela & Berger, 2012; Thompson & Norton, 2011; Thompson et al., 2005). For example, they focus on the impact of feature number on consumers' perceived product usefulness and choice (Sela & Berger, 2012); perceived product capability, usability, and utility (Thompson et al., 2005); perceived social utility and choice (Thompson & Norton, 2011); or perceived satisfaction and choice (Goodman & Irmak, 2013). These studies provide important insights into the impact of the number of product features on consumer attitudes and downstream variables. However, the literature is silent on the corresponding impact of other dimensions that also constitute a product's complexity, such as the heterogeneity and interrelatedness of product features. This research gap is lamentable because it impedes insights into whether these neglected dimensions of product complexity favorably or unfavorably affect consumer attitudes and downstream variables, as well as whether they strengthen or weaken the corresponding impact of the number of features. Insights into these issues could help managers optimize new product design, advertising, and selling, thus fostering consumer product adoption.

To address this important research gap, this article examines the effects and interplay of multiple dimensions of a product's structural complexity on consumer attitudes and intentions, thus representing the first investigation of consumer perceptions of product complexity beyond pure feature number. For this purpose, we draw on systems theory to identify two additional dimensions of product complexity: the *heterogeneity of product features* (i.e., the extent of functional dissimilarity of features) and the *interrelatedness of product features* (i.e., the extent of functional connectivity of features). Using a state-of-practice market analysis of existing products for two product categories (smart home systems and smartphones) and four experiments, we examine whether and how these dimensions affect consumer attitudes (expected product capability and usability) and, in turn, purchase intention, both separately and in conjunction with the number of product features.

This article extends the literature in several ways. First, it shows that, analogous to other functional areas such as R&D and manufacturing, marketing must consider the downstream effects not only of the number of product features but also of other dimensions of product complexity, particularly the heterogeneity and interrelatedness of product features. In addition to providing marketing researchers with more explicit levers for new product design, advertising, and selling, these findings contribute to a more holistic approach to product complexity management that considers both the impact of multiple complexity dimensions on internal processes and costs and the impact of these dimensions on consumer product adoption. Second, this article offers a thorough understanding of the impact of the various dimensions of product complexity on consumer product adoption. We show that not only the number of product features but also the heterogeneity and interrelatedness of these features influence consumer attitudes and intentions, thereby revealing that these novel dimensions have discrete and somewhat different effects on consumer product adoption. Third, this research provides a detailed understanding of the interplay between the various dimensions of product complexity. It provides evidence that both feature heterogeneity and feature interrelatedness moderate the downstream effects of number of features but that they do so in fundamentally different ways. We thereby extend prior knowledge by showing that a product with the same number of product features can lead to significantly different consumer attitudes and intentions. Overall, this article explains why marketing researchers' focus should shift from examining the impact of the pure number of product features on consumer product adoption to also assessing the corresponding impact of the heterogeneity and interrelatedness of these features and the interplay between these dimensions of product complexity.

Development of conceptual framework

Dimensions of product complexity

To develop our multidimensional conceptualization of product complexity, we draw on systems theory (Von Bertalanffy, 1968), which research has previously applied to describe, for example, the complexity of organizations and their environment (Achrol & Stern, 1988; Duncan, 1972; Thompson, 1967) and multi-channel systems (Fürst & Scholl, 2022). This theory suggests that every system (e.g., a product) consists of structural elements (e.g., features) that can be characterized according to three criteria – that is, "according to their number" but also "according to their species" and "according to the relations of elements" (Von Bertalanffy, 1968, p. 54). Because a product offers certain functions to perform, the species of its elements could, for example, refer to the functional dissimilarity (i.e., heterogeneity) of features in type or nature and the relations of its elements, for example, to the functional connectivity (i.e., interrelatedness) of features. Thus, systems theory indicates that not only the number of features but also the heterogeneity and interrelatedness of these features determine a product's structural complexity. Therefore, a product with a specific number of features that are highly heterogeneous and highly interrelated is characterized by greater structural complexity than a product with the same number of features that are less heterogeneous and less interrelated. Consequently, according to systems theory, prior studies' singular focus on the *number of product features* (e.g., Sela & Berger, 2012; Thompson et al., 2005) does not fully capture the construct of product complexity.

The *heterogeneity of product features* reflects the dissimilarity of structural elements inherent in a product to perform specific functions (Duncan, 1972; Lee & Chu, 2021; Thompson, 1967). Studies on the addition of a new feature to an existing product indicate that a feature can be characterized as more or less similar to the base product in terms of the benefits and value it offers (Gattol et al., 2016; Lee & Chu, 2021). Therefore, in the context of our research, the heterogeneity of product features can be described by the overall dissimilarity of features in terms of the purpose they serve. For example, in a smart home system, the features of "floor heating," "fridge," and "television" are very dissimilar and, thus, highly heterogeneous, as they refer to the control of housing, household, and entertainment technologies, respectively. By contrast, "floor heating," "ventilation," and "air conditioning" all refer to housing technology, which makes them considerably less dissimilar and, thus, less heterogeneous.

The *interrelatedness of product features* captures the connectivity of structural elements inherent in a product to perform specific functions (Duncan, 1972; Pinochet et al., 2018; Thompson, 1967). Similar to components of product offerings that can be linked together to enable them to communicate and work with each other (Chang et al., 2014; Pinochet et al., 2018), we assume that the features of a product can be connected, which allows them to exchange data, and thus their use can be combined. The functional connectivity of a product's totality of features refers to the proportion of connections between features. Based on the concept of network density (Gupta et al., 2019; Scott, 1988), it is determined by the actual quantity of connections between features compared with the maximum quantity of connections between features. For example, in a smart home system, the features of "television," "multiroom audio," and "blinds" could all be connected, such that if "television" is used, "multiroom audio" is automatically activated (or deactivated) and "blinds" go down, representing a high interrelatedness of features. Conversely, these features could also lack any corresponding connections because of, for example, missing technical interfaces or compatibilities, which would indicate low interrelatedness of features.

Previous research has not investigated the heterogeneity and interrelatedness of product features, which is unfortunate because examining them in addition to and together with the number of product features would allow for a more comprehensive conceptualization of product complexity and thus provide a fuller picture of levers for product design, advertising, and selling. In this context, it is important to note that all three dimensions are characteristic of complex products, as they derive from systems theory, which deals with the structural aspects of complexity, and they are distinct because a product can, for example, have features that are high in heterogeneity but either high or low in interrelatedness. Herein, we empirically verify the distinctiveness of these dimensions.

Consumer attitudes

To select the consumer attitudes for our framework, we draw on a benefit–cost logic (Johnson & Payne, 1985; Payne, 1982), which suggests that consumers assess a product depending on their benefit- and cost-related needs (De Angelis & Carpenter, 2009). According to this logic, the beliefs resulting from product assessment refer to benefits, such as consumers' expected gain from the product, and costs, such as consumers' expected effort, time, and energy for learning about and using the product (Mukherjee & Hoyer, 2001). Thus, consistent with the selection of similar pairs of constructs by previous research on consumer perceptions of product complexity (Thompson et al., 2005) and technology acceptance (Blut et al., 2016), our framework focuses on product capability (a consumer benefit from the product) and product usability (a consumer cost of learning about and using the product). Because our focus is on products new to the consumer, these constructs relate to expectations rather than actual experiences. *Expected product capability* refers to consumers' beliefs about the product's ability to perform desired tasks (Thompson & Norton, 2011; Thompson et al., 2005). *Expected product usability* reflects consumers' beliefs about the ease of learning and using the product (Davis, 1989; Thompson et al., 2005). Typically, consumers view a product's capability and usability as competing needs when forming their purchase decisions (Blut et al., 2016; Thompson et al., 2005). For example, Davis (1989, p. 320) argue that "even if potential users believe that a given application is useful, they may, at the same time, believe that the system is too hard to use and that the performance benefits of usage are outweighed by the effort of using the application." Thus, their choice represents the result of a "cognitive trade-off between the effort required … (i.e., ease of use) and the quality (i.e., usefulness) of the resulting [choice] decision" (Kim et al., 2007, p. 115). To ensure new product adoption, examining whether feature heterogeneity and interrelatedness enhance consumers' expected product capability or whether they predominantly reduce consumers' perceived product usability is therefore highly managerially relevant (Nysveen et al., 2005; Sääksjärvi & Samiee, 2011).

Consumer intentions

Our framework includes *product purchase intention* as the primary downstream variable. This construct refers to the extent to which consumers are willing to buy a product (Dodds et al., 1991).

Overview of framework

Figure 1 shows our framework, including the hypothesized effects. Our focal hypotheses relate to the main and moderating effects of the two novel dimensions of product complexity

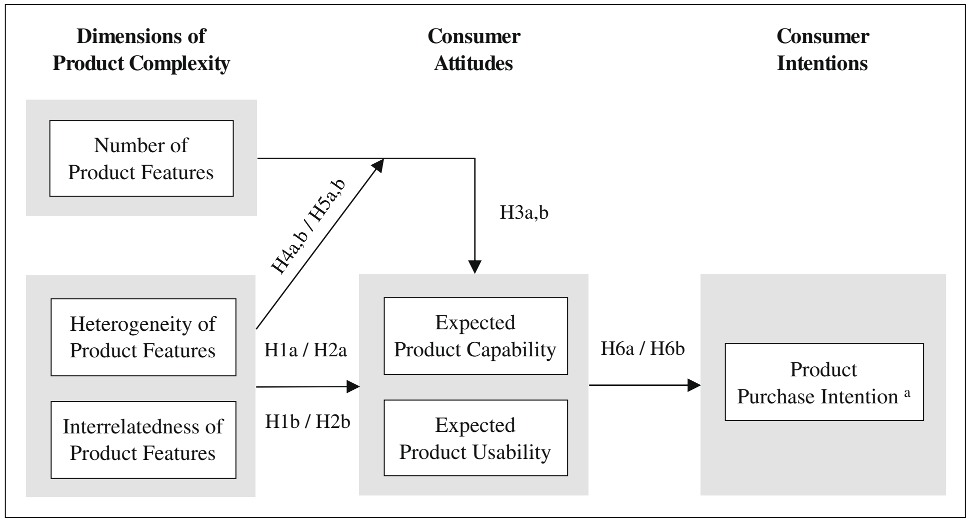

Fig. 1 Conceptual framework. [a] Alternatively: Expected product utility or product purchase behavior

(i.e., heterogeneity and interrelatedness of product features). In terms of main effects, we predict that both dimensions increase expected product capability and decrease expected product usability, both of which are assumed to promote product purchase intention. In Study 1a (smart home context) and, for replication purposes, Study 1b (smartphone context), we concentrate on the direct main effects of these dimensions on consumer attitudes (H1a/b, H2a/b) while holding constant the number of product features. In terms of moderating effects, we predict that both heterogeneity and interrelatedness of product features will increase the positive impact of number of product features on expected product capability and the negative impact of number of product features on expected product usability. Study 2a (smart home context) and, for replication purposes, Study 2b (smartphone context) focus on testing these moderating effects (H4a/b, H5a/b) and related main effects (H3a/b), thereby manipulating not only heterogeneity and interrelatedness but also the number of product features. In addition, these studies validate Studies 1a's and 1b's findings related to the direct main effects of the two novel dimensions (H1a/b, H2a/b) and examine their corresponding downstream effects on consumer purchase intentions (H6a/b).

Hypotheses development

Effects of heterogeneity of product features

High heterogeneity of product features indicates to consumers that the product can perform a wide variety of functions. For example, a smart home system that controls not only supply functions and related housing technology but also housework functions and related household technology, as well as enjoyment functions and related entertainment technology, offers a broad range of functions and, thus, increased expected benefits for consumers. In line with this reasoning, previous research suggests that dissimilar features may enact more different roles in a product than similar ones and thus are able to deliver more value (Gibbert & Mazursky, 2009; Kuehnl et al., 2017; Wilkenfeld & Ward, 2001). Therefore, consumers are likely to infer a broad range of functions from highly heterogeneous features and, thus, high ability of the product to perform desired tasks, which enhances their expected product capability.

However, high heterogeneity of product features also means that consumers are less likely to assign the features to the same group and more likely to consider them separate entities, which requires significant time and energy to engage with the product (Mukherjee & Hoyer, 2001; Shugan, 1980). For example, a smart home system that allows control of not only housing technology but also household technology and entertainment technology offers very different types of functions that may entail high expected costs for customers to learn and use the product. In support of this argumentation, previous research suggests that consumers have more difficulty categorizing and making sense of dissimilar product features than similar ones (Gibbert & Mazursky, 2009; Wilkenfeld & Ward, 2001). Therefore, highly heterogeneous features tend to complicate processing, which makes consumers anticipate considerable costs of learning and using a product, thereby decreasing their expected product usability. Thus, we predict the following:

H1 The heterogeneity of product features (a) increases expected product capability and (b) decreases expected product usability.

Effects of interrelatedness of product features

High interrelatedness of product features enables the exchange of data between features and, thus, their combined use, which allows consumers to take advantage of functions that would not be feasible otherwise. For example, a smart home system in which the features of "television," "multiroom audio," and "blinds" are connected enables consumers using "television" to turn on (or off) "multiroom audio" automatically and have "blinds" go down, leading to enhanced functions and, thus, greater expected benefits. Consistent with this reasoning, previous research suggested that products that are connected with each other in a network are able to carry out additional tasks that are more comprehensive and sophisticated, thus providing added value (Chang et al., 2014; Hoffman & Novak, 2018; Raff et al., 2020). Consequently, consumers are likely to anticipate enhanced functions from highly interrelated features, which fosters their belief about the product's capability.

However, consumers may also perceive high interrelatedness of product features as offering an almost incomprehensible multitude of possible connections between features they could activate when setting up the product or apply when using the product, which likely requires considerable time and energy to understand the product and make use of its full potential (Mukherjee & Hoyer, 2001; Shugan, 1980). For example, a smart home system with 10 highly interrelated features could easily offer 15–20 connections between features to consider, resulting in significant expected costs for customers to learn and use the product. Previous research indicates that "as the number of [connections] … increases, the memory structure for [the product] … becomes richer, but also more complex" (Krishnan, 1996, p. 392), and the more connections between features to take into account, the higher are consumers' inferences about costs of learning and using the product (Buescher et al., 2009; Meyer et al., 2008). Consequently, highly interrelated features likely complicate processing, which causes consumers to anticipate significant costs of learning and using the product, thereby reducing their expected product usability. Thus:

H2 The interrelatedness of product features (a) increases expected product capability and (b) decreases expected product usability.

Effects of number of product features

Although the main effects of feature number on consumer attitudes are not the focus of our study (for a previous study on feature number, see Thompson et al., 2005), we present a brief reasoning for corresponding hypotheses, which serves as a baseline for the moderating effects of our two dimensions of interest on these main effects. A high number of features signals to consumers that the product can perform a multitude of functions. In support of this reasoning, previous research indicates that consumers typically infer the quantity of functions and the related benefits from the features of a product (Bertini et al., 2009; Nowlis & Simonson, 1996). Therefore, consumers are likely to have stronger beliefs that a feature-rich product is able to perform desired tasks better than a feature-poor product, resulting in a higher expected product capability.

However, a high number of features and the resulting multitude of functions indicates to consumers that the product will have a large number of decision and usage options for which they must invest considerable effort, time, and energy to understand and make full use of the product (Bettman et al., 1991; Iyengar & Lepper, 2000; Meyer et al., 2008). This argumentation is consistent with prior research showing that a high quantity of functions is associated with a large number of decision and usage options that decrease consumers' ability to understand and use the product (Ji et al., 2006; Preece et al., 2002), thereby causing them to infer high learning costs and develop fears of erroneous product use (Goodman & Irmak, 2013; Meyer et al., 2008). Thus, a feature-rich product likely overwhelms consumers, which can lead them to assume considerable difficulty of learning and using the product and thus decrease their expected product usability. Therefore, building on Thompson et al. (2005), we predict the following:

H3 The number of product features (a) increases expected product capability and (b) decreases expected product usability.

Previously, we argued that the number of features drives consumers' perceived quantity of functions that a product provides, which increases expected product capability and reduces expected product usability (Bertini et al., 2009; Meyer et al., 2008). Subsequently, we argue that the number of features drives consumers' perceived quantity of functions to varying degrees depending on the heterogeneity and interrelatedness of these features, which ultimately affects the strength of the impact of feature number on expected product capability and usability.

In terms of the moderating effect of feature heterogeneity, prior research suggests that dissimilar features tend to have different functional roles in a product whereas similar features tend to compete for the same functional roles (Estes, 2003; Gibbert & Mazursky, 2009; Wilkenfeld & Ward, 2001). Thus, when increasing the number of dissimilar features by a certain amount, this increase tends to result in less overlap in functions of the product than when increasing the number of similar features by the same amount, leading to a stronger growth in consumers' perceived quantity of functions. This stronger growth in the perceived quantity of functions is, in turn, likely to lead to a stronger increase in consumers' expectation of the product's ability to perform desired tasks and their decision and usage effort and, thus, time and energy to understand and make use of the product (De Angelis & Carpenter, 2009; Goodman & Irmak, 2013). Thus, when feature heterogeneity is high (vs. low), increasing the number of features tends to disproportionately enhance expected product capability and reduce expected product usability.

In terms of the moderating effect of feature interrelatedness, previous studies indicate that the more interrelated the features of a product, the more connections they have, which allows them to better interact with each other and work together, resulting in more functions (Estes, 2003; Ng & Wakenshaw, 2017; Pinochet et al., 2018). Therefore, increasing the number of highly interrelated features by a certain amount tends to create more additional connections in the product than increasing the number of less interrelated features by the same amount, resulting in a stronger growth in consumers' perceived quantity of functions. The stronger growth in the perceived quantity of functions is, in turn, likely to result in a stronger increase in consumers' expectation of the product's ability to perform desired tasks and their costs of learning and using the product (De Angelis & Carpenter, 2009; Goodman & Irmak, 2013). Consequently, when feature interrelatedness is high (vs. low), increasing the number of features tends to disproportionately increase expected product capability and decrease expected product usability. Overall, we predict the following:

H4 When the heterogeneity of product features is high rather than low, the number of product features (a) increases expected product capability more strongly and (b) decreases expected product usability more strongly.

H5 When the interrelatedness of product features is high rather than low, the number of product features (a) increases expected product capability more strongly and (b) decreases expected product usability more strongly.

Effects of consumer attitudes

Extant research indicates that consumers consider the costs and benefits associated with a product when forming their intentions (Johnson & Payne, 1985; Payne, 1982). Therefore, and supported by prior research showing that anticipated product usability and capability enhance expected utility (Thompson et al., 2005) and intention to use (Nysveen et al., 2005), we predict the following:

H6 Product purchase intention is increased by (a) expected product capability and (b) expected product usability.

Development of stimuli

To ensure realistic descriptions in our scenarios, we conducted an extensive state-of-practice market analysis. Our sample consisted of smart home systems and smartphones that reflect the range of products available on the market and differ significantly in their complexity. This differentiation is in line with suppliers that classify products of these types as either basic or complex feature systems. We carefully scrutinized product manuals, created a list of features for each product, and then analyzed the features in terms of their number, heterogeneity, and interrelatedness.

Stimuli for number of product features

Drawing on prior studies' operationalizations (Thompson & Norton, 2011; Thompson et al., 2005), our analyses of the manuals, and a pretest, we determined the number of features to be 5 for the "low number of features" condition, 10 for the "medium number of features" condition, and 15 for the "high number of features" condition.

Stimuli for heterogeneity of product features

To develop the "low heterogeneity of features" and "high heterogeneity of features" conditions, we performed several steps. First, we searched for an appropriate criterion to determine product feature heterogeneity. Our analyses of the manuals showed that products differ especially in the extent to which their features belong to the same functional category or to different functional categories. In the case of smart home systems, the features were primarily related to the control of housing technology, though some were also related to the control of household and entertainment technology. For smartphones, the features mainly belonged to communication, though some also belonged to organization and entertainment. Second, we designed the "low heterogeneity of features" condition to consist of features of the same functional category serving a similar purpose (i.e., control of housing technology in the smart home context and communication in the smartphone context), while the "high heterogeneity of features" condition included features from three functional categories serving different purposes (i.e., control of housing technology, household technology, and entertainment technology in the smart home context and communication, organization, and entertainment in the smartphone context). Third, we drew on Blau's (1977) index of heterogeneity to verify the extent of heterogeneity for both conditions (see part A1 in Appendix 1).

Stimuli for interrelatedness of product features

To determine the specific quantity of connections between features for "low interrelatedness of features" and "high interrelatedness of features," we used a multistep approach that draws on the concept of network density (Gupta et al., 2019; Scott, 1988). First, we calculated the maximum quantity of connections between features c_{max} for the three conditions of number of product features (see part A2 in Appendix 1). Second, we aimed to find recommendations from the literature for determining the proportion of the maximum quantity of connections pc_i that should represent a “low interrelatedness of features” and “high interrelatedness of features,” respectively. Yet work on network analysis emphasizes the absence of any universal threshold values or rule of thumb, because “the assessment of the actual density [i.e., interrelatedness of elements] … must take account of the size of the network [i.e., number of elements]” (Scott, 1988, p. 115). Specifically, in a network with a large number of elements, a high proportion of connections between elements is typically less feasible or useful than in a network with a small number of elements (Scott, 1988). Therefore, studies on network analysis recommend that for a larger number of elements, it is best to rely on lower values as an indicator of high density than for a smaller number of elements, such that even “a density of 0.29 may, under certain circumstances, indicate a very high level of cohesion [i.e., connectivity] in the network” (Scott, 1988, p. 115). Moreover, even with an objectively low density of, for example, 0.10, a network with a larger number of elements may be perceived as highly cohesive because of the relatively large absolute quantity of connections. Thus, in the context of our study, the literature recommends that products with a larger number of features should generally apply lower proportion values of the maximum quantity of connections pc_i as an indicator of high and low interrelatedness than products with a smaller number of features (Bandyopadhyay et al., 2010). Third, following these recommendations and supported by our analysis of product manuals and a pretest, we discounted the proportion value pc_i for the “high number of features” condition by the factor 2 compared with the “low number of features” condition (see part A2 in Appendix 1). Finally, we primarily drew on our analysis of product manuals and a short pretest ($n=22$; 50% female, $M_{age}=31.91$ years) to determine which specific features to present in our scenarios as functionally connected.

Studies 1a and 1b: Main effects of novel dimensions of product complexity

Method

Goals, design, and participants To examine the impact of heterogeneity and interrelatedness of product features on consumer attitudes (H1a/b, H2a/b), we conducted Study 1a in a smart home context and, for replication purposes, Study 1b in a smartphone context. In both studies, we randomly assigned consumers (SH: $n=240$; 49% female, $M_{age}=44.80$ years; SP: $n=195$; 50% female, $M_{age}=44.90$ years) from a representative access panel of a professional market research institute (Respondi) to a 2 (heterogeneity of features: low vs. high) × 2 (interrelatedness of features: low vs. high) between-subjects design. Participants received points from the panel provider as incentives. Drawing on our stimulus development and a successful pretest of our manipulations (see Appendix 2, part B1), we manipulated all independent variables (i.e., the two novel dimensions of product complexity) and held the number of features constant on a medium level. The latter was necessary to analyze the mere effects of heterogeneity and interrelatedness of features.

Procedure and measures We conducted a computer-based experiment. First, participants answered questions related to demographics (e.g., age, gender, educational level). Second, we introduced the session as a study on purchase decisions and asked participants to imagine that they were interested in purchasing a new smart home system (in Study 1a) or smartphone (in Study 1b). Subsequently, as shown in parts C1, C3, and C4 of the Supplemental Material, we presented the stimuli including an initial description that explained the underlying logic of the stimuli. To manipulate the product complexity dimensions, we did not mention their labels (heterogeneity and interrelatedness) but primarily relied on visual elements (shapes, colors, and lines with arrows) combined with a verbal listing of the features and their categories. Specifically, to manipulate “heterogeneity,” the features of each category (e.g., in the smart home context: housing technology features, household features, entertainment features) had a unique shape and color and were grouped together in the form of a list on the upper part of the respective stimulus. To manipulate “interrelatedness,” the corresponding features were linked by a line with double-sided arrows. Depending on the scenario, the presented product varied in heterogeneity and interrelatedness of features, while the number of features (medium level) remained constant. Third, we asked questions related to the manipulation check, psychographics (consumer expertise and, in Study 1a, trust), and consumer attitudes (expected product capability and usability). Part B2 in Appendix 2 provides an overview of the scales and their reliability; part B3 shows that corresponding checks provided sufficient support for our manipulations.

Results

We performed a 2 × 2 multivariate analysis of covariance (MANCOVA) with heterogeneity and interrelatedness of features as independent variables and expected product capability and usability as dependent variables. As controls, we included demographics (age, gender, and educational level) and, following Thompson et al. (2005), consumer expertise. We found no support for H1a that heterogeneity of features increases expected product capability (SH: $M_{low\ hete}=4.48$, $SD=1.60$ vs. $M_{high\ hete}=4.15$, $SD=1.78$; $F(1, 231)=2.67$, $p=0.10$; SP: $M_{low\ hete}=4.38$, $SD=1.51$ vs. $M_{high\ hete}=4.20$, $SD=1.34$; $F(1, 186)=1.05$, $p=0.31$). However, the data showed full support for the predicted negative effect of heterogeneity of features on expected product usability (SH: $M_{low\ hete}=4.48$, $SD=1.50$ vs. $M_{high\ hete}=4.03$, $SD=1.77$; $F(1, 231)=6.09$, $p<0.05$; SP: $M_{low\ hete}=5.71$, $SD=1.21$ vs. $M_{high\ hete}=5.25$, $SD=1.18$; $F(1, 186)=8.13$, $p<0.05$), confirming H1b.

In addition, the results provided full support that interrelatedness of features increases expected product capability (SH: $M_{low\ inter}=4.08$, $SD=1.63$ vs. $M_{high\ inter}=4.55$, $SD=1.71$; $F(1, 231)=4.81$, $p<0.05$; SP: $M_{low\ inter}=3.87$, $SD=1.42$ vs. $M_{high\ inter}=4.72$, $SD=1.21$; $F(1, 186)=20.01$, $p<0.01$). Moreover, we found that interrelatedness of features decreases expected product usability (SH: $M_{low\ inter}=4.51$, $SD=1.45$ vs. $M_{high\ inter}=4.00$, $SD=1.82$; $F(1, 231)=6.80$, $p<0.05$; SP: $M_{low\ inter}=5.66$, $SD=1.06$ vs. $M_{high\ inter}=5.30$, $SD=1.36$; $F(1, 186)=4.48$, $p<0.05$). Thus, the data confirmed H2a and H2b. For both product categories, the interaction effects of heterogeneity and interrelatedness on expected capability and expected usability, respectively, were nonsignificant. Figure 2 provides an overview of the effects of the two novel dimensions of product complexity on consumer attitudes.

Discussion

Studies 1a and 1b showed that both feature heterogeneity and interrelatedness have a discrete impact on consumer attitudes. In this context, we found similarities and differences in how these novel dimensions of product complexity affect expected product capability and usability. While both dimensions decrease expected product usability, only feature interrelatedness increases expected product capability. A possible explanation for the finding that feature heterogeneity does not increase expected product capability is that consumers lack trust that products offered to them with a high dissimilarity of features will actually be able to provide the proposed capability. To test this assumption, we estimated a mediation model based on 10,000 bootstrap samples (Hayes, 2018, PROCESS Model 4). In support of our assumption, the results confirmed that feature heterogeneity decreases consumer trust and, in turn, expected product capability (indirect effect: $b=-0.39$, SE (boot) $=0.16$, 95% CI $=[-0.71; -0.08]$), which mitigates any positive effects of feature heterogeneity on expected product capability.

Overall, studies 1a and 1b highlight the importance of extending the previously unidimensional conceptualization of product complexity to a multidimensional view that includes not only number of product features but also their heterogeneity and interrelatedness. Studies 2a and 2b draw on this three-dimensional conceptualization of product complexity to develop a detailed understanding of the impact and interplay of the two novel dimensions and the well-known dimension.

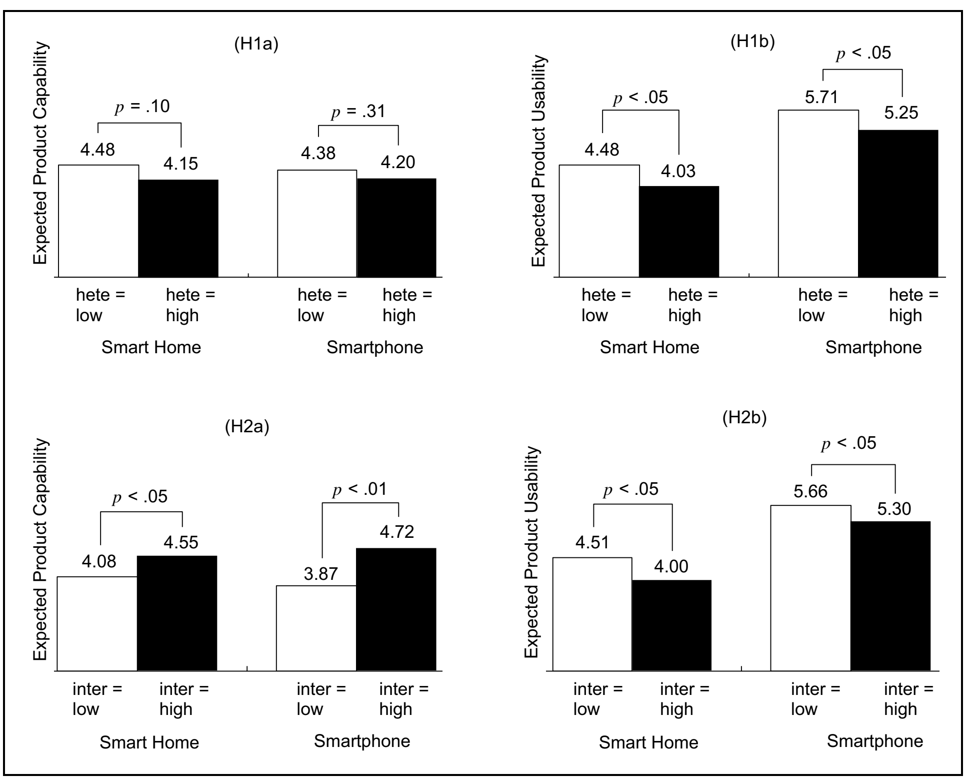

Fig. 2 Main effects of novel dimensions of product complexity. hete = heterogeneity of features; inter = interrelatedness of features; number of features was held constant

Studies 2a and 2b: Moderating effects of novel dimensions of product complexity

Method

Goals, design, and participants First, Studies 2a (smart home context) and 2b (smartphone context) aimed to validate the findings of Studies 1a and 1b related to the direct main effects of heterogeneity and interrelatedness of features on consumer attitudes (H1a/b, H2a/b) and to analyze related downstream effects on consumer intentions (H6a/b). Second, and more important, we performed these studies to investigate the moderating effects of heterogeneity and interrelatedness of features (H4a/b, H5a/b) on the corresponding impact of number of features (H3a/b). From a representative access panel of professional market research institute (Respondi), we obtained participants (SH: n = 439; 52% female, M_{age} = 44.59 years; SP: n = 449; 53% female, M_{age} = 45.60 years) and randomly assigned them to a 2 (number of features: low vs. high) × 2 (heterogeneity of features: low vs. high) × 2 (interrelatedness of features: low vs. high) between-subjects design. As in Studies 1a and 1b, participants received points from the panel provider as incentives. Relying on our stimulus development and a successful pretest of our manipulations (see Appendix 3, part C1), we manipulated all independent variables (i.e., the three dimensions of product complexity).

Procedure and measures We measured some demographics (e.g., age, gender, educational level) and then used the same experimental procedure as in Studies 1a and 1b. After presenting the stimuli (see parts C2, C5, and C6 of the Supplemental Material), we asked questions related to the manipulation check, psychographics (consumer expertise and, in Study 2a, trust), consumer attitudes (expected product capability and usability), and product purchase intention. In Appendix 3, part C2, we show details on the scales and their reliability. Moreover, part C3 provides an overview of our manipulation checks, which provided sufficient support for the appropriateness of our stimuli.

Results

Test of hypotheses We conducted a 2 × 2 × 2 MANCOVA with number, heterogeneity, and interrelatedness of features as independent variables and age, gender, educational level, and consumer expertise as controls on expected product capability and usability. For the hypothesized main effects and consistent with Studies 1a and 1b, we found no support for H1a that feature heterogeneity increases product capability (SH: $M_{low\ hete}$ = 4.48, SD = 1.62 vs. $M_{high\ hete}$ = 4.21, SD = 1.56; $F(1, 427)$ = 3.66, p = 0.06; SP: $M_{low\ hete}$ = 4.07, SD = 1.53 vs. $M_{high\ hete}$ = 4.17, SD = 1.51; $F(1, 437)$ = 0.58, p = 0.45). Also consistent with Studies 1a and 1b, we found ample evidence that feature heterogeneity decreases product usability (SH: $M_{low\ hete}$ = 4.45, SD = 1.65 vs. $M_{high\ hete}$ = 4.17, SD = 1.63; $F(1, 427)$ = 4.51, $p < 0.05$; SP: $M_{low\ hete}$ = 5.42, SD = 1.28 vs. $M_{high\ hete}$ = 5.17, SD = 1.48; $F(1, 437)$ = 5.37, $p < 0.05$), in support of H1b.

In addition, the data provided full support that feature interrelatedness increases product capability (SH: $M_{low\ inter}$ = 4.06, SD = 1.58 vs. $M_{high\ inter}$ = 4.63, SD = 1.57; $F(1, 427)$ = 16.28, $p < 0.01$; SP: $M_{low\ inter}$ = 3.66, SD = 1.52 vs. $M_{high\ inter}$ = 4.59, SD = 1.35; $F(1, 437)$ = 50.18, $p < 0.01$). Moreover, we found that feature interrelatedness decreases product usability (SH: $M_{low\ inter}$ = 4.53, SD = 1.60 vs. $M_{high\ inter}$ = 4.09, SD = 1.67; $F(1, 427)$ = 10.69, $p < 0.01$; SP: $M_{low\ inter}$ = 5.43, SD = 1.32 vs. $M_{high\ inter}$ = 5.15, SD = 1.42; $F(1, 437)$ = 7.00, $p < 0.05$). Thus, consistent with Studies 1a and 1b, H2a and H2b were confirmed.

As predicted, we also found ample evidence that feature number increases product capability (SH: $M_{low\ num}$ = 4.12, SD = 1.65 vs. $M_{high\ num}$ = 4.57, SD = 1.51; $F(1, 427)$ = 10.10, $p < 0.01$; SP: $M_{low\ num}$ = 3.76, SD = 1.53 vs. $M_{high\ num}$ = 4.48, SD = 1.42; $F(1, 437)$ = 31.17, $p < 0.01$). Moreover, the data show that feature number decreases product usability (SH: $M_{low\ num}$ = 4.77, SD = 1.62 vs. $M_{high\ num}$ = 3.84, SD = 1.55; $F(1, 427)$ = 48.28, $p < 0.01$; SP: $M_{low\ num}$ = 5.74, SD = 1.07 vs. $M_{high\ num}$ = 4.84, SD = 1.50; $F(1, 437)$ = 69.63, $p < 0.01$). Thus, H3a and H3b were supported.

Moreover, we tested for the hypothesized moderating effects. Figures 3 and 4 provide a graphical overview of our results related to these moderating effects. For product capability, the results did not provide evidence for H4a, which predicted an interaction between feature number and heterogeneity (SH: $F(1, 427)$ = 0.35, p = 0.56; SP: $F(1, 437)$ = 0.54, p = 0.46). By contrast, we found evidence for H4b, which proposed an interaction effect of feature number and interrelatedness on product capability (SH: $F(1, 427)$ = 5.47, $p < 0.05$; SP: $F(1, 437)$ = 5.01, $p < 0.05$). Specifically, as predicted, feature number increases product capability more strongly when feature interrelatedness is high (SH: $M_{low\ num}$ = 4.24, SD = 1.72 vs. $M_{high\ num}$ = 5.02, SD = 1.28; $F(1, 427)$ = 14.97, $p < 0.01$; SP: $M_{low\ num}$ = 4.08, SD = 1.40 vs. $M_{high\ num}$ = 5.09, SD = 1.11; $F(1, 437)$ = 30.04, $p < 0.01$) rather than low (SH: $M_{low\ num}$ = 4.00, SD = 1.58 vs. $M_{high\ num}$ = 4.12, SD = 1.58; $F(1, 427)$ = 0.36, p = 0.55; SP: $M_{low\ num}$ = 3.44, SD = 1.57 vs. $M_{high\ num}$ = 3.87, SD = 1.43; $F(1, 437)$ = 5.62, $p < 0.05$). In addition, we found an interaction between heterogeneity and interrelatedness in the smartphone context (SP: $F(1, 437)$ = 7.34, $p < 0.05$), but not in the smart home context (SH: $F(1, 427)$ = 0.07, p = 0.79), and no evidence of a three-way-interaction (SH: $F(1, 427)$ = 1.79, p = 0.18; SP: $F(1, 437)$ = 0.55, p = 0.46).

For product usability, we found a significant interaction between feature number and heterogeneity (SH: F(1,

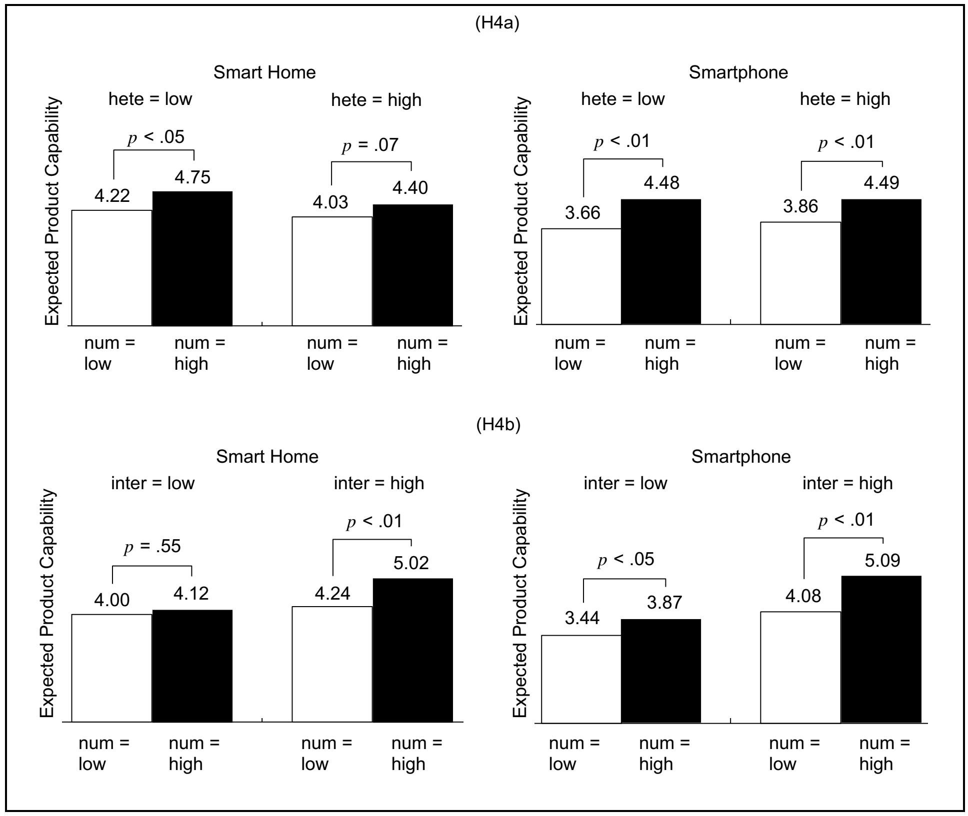

Fig. 3 Moderating effects of novel dimensions of product complexity on expected product capability. hete = heterogeneity of features; inter = interrelatedness of features; num = number of features

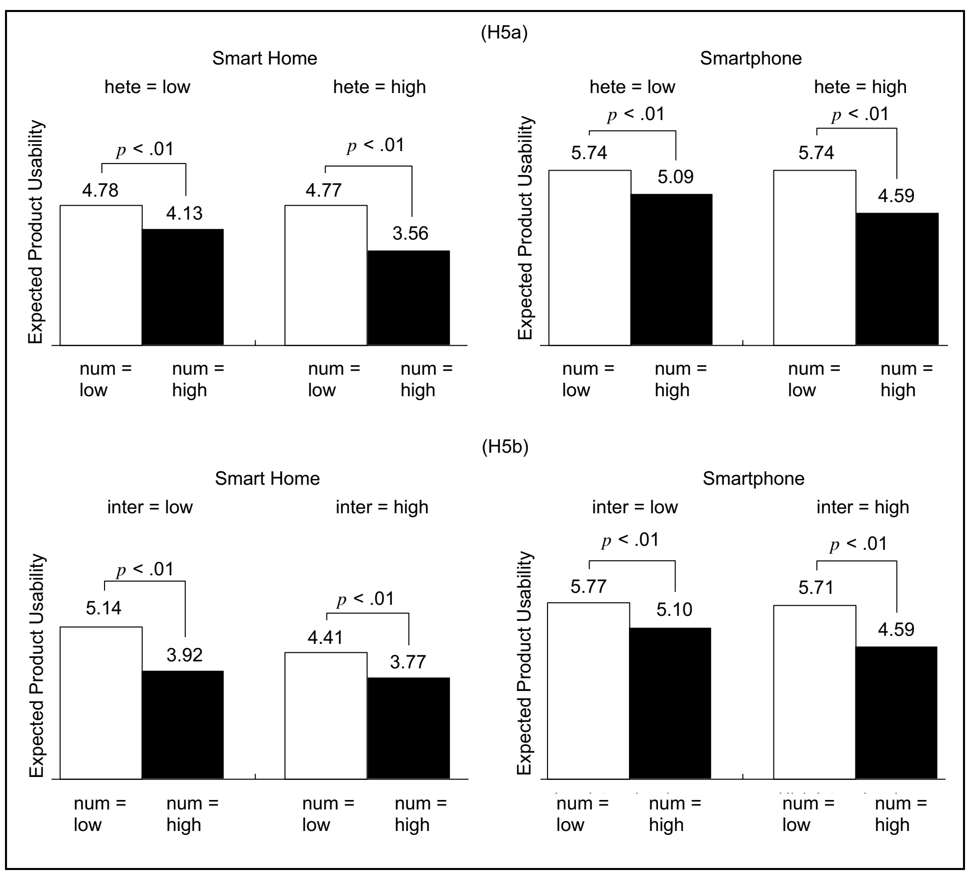

Fig. 4 Moderating effects of novel dimensions of product complexity on expected product usability. hete = heterogeneity of features; inter = interrelatedness of features: num = number of features

427) = 4.36, $p < 0.05$; SP: $F(1, 437) = 5.18$, $p < 0.05$). Specifically, as predicted in H5a, feature number decreases product usability more strongly when feature heterogeneity is high (SH: $M_{low\ num} = 4.77$, $SD = 1.57$ vs. $M_{high\ num} = 3.56$, $SD = 1.42$; $F(1, 427) = 40.47$, $p < 0.01$; SP: $M_{low\ num} = 5.74$, $SD = 1.02$ vs. $M_{high\ num} = 4.59$, $SD = 1.54$; $F(1, 437) = 53.86$, $p < 0.01$) rather than low (SH: $M_{low\ num} = 4.78$, $SD = 1.68$ vs. $M_{high\ num} = 4.13$, $SD = 1.58$; $F(1, 427) = 11.82$, $p < 0.01$; SP: $M_{low\ num} = 5.74$, $SD = 1.11$ vs. $M_{high\ num} = 5.09$, $SD = 1.38$; $F(1, 437) = 19.01$, $p < 0.01$). Moreover, we found support for H5b, proposing an interaction effect of feature number and interrelatedness on product usability (SH: $F(1, 427) = 4.64$, $p < 0.05$; SP: $F(1, 437) = 4.47$, $p < 0.05$). As expected, in the smartphone context, feature number decreases product usability more strongly when feature interrelatedness is high (SP: $M_{low\ num} = 5.71$, $SD = 0.92$ vs. $M_{high\ num} = 4.59$, $SD = 1.54$; $F(1, 437) = 53.68$, $p < 0.01$) rather than low (SP: $M_{low\ num} = 5.77$, $SD = 1.17$ vs. $M_{high\ num} = 5.10$, $SD = 1.38$; $F(1, 437) = 19.57$, $p < 0.01$). By contrast, in the smart home context, feature number decreases product usability less strongly when interrelatedness is high (SH: $M_{low\ num} = 4.41$, $SD = 1.74$ vs. $M_{high\ num} = 3.77$, $SD = 1.54$; $F(1, 427) = 11.29$, $p < 0.01$) rather than low (SH: $M_{low\ num} = 5.14$, $SD = 1.41$ vs. $M_{high\ num} = 3.92$, $SD = 1.56$; $F(1, 427) = 42.10$, $p < 0.01$). Thus, overall, we found partial support for H5b. In addition, we found that neither the interaction between feature heterogeneity and interrelatedness (SH: $F(1, 427) = 0.29$, $p = 0.59$; SP: $F(1, 437) = 0.41$, $p = 0.53$) nor the three-way interaction was significant (SH: $F(1, 427) = 0.32$, $p = 0.57$; SP: $F(1, 437) = 1.52$, $p = 0.22$).

Finally, we performed a regression analysis to test the hypothesized effects of expected product capability and usability on product purchase intention, again controlling for demographics (age, gender, and educational level) and consumer expertise. Our findings indicated that product purchase intention is increased by both product capability (SH: $\beta = 0.56$, $p < 0.01$; SP: $\beta = 0.65$, $p < 0.01$) and usability (SH: $\beta = 0.11$, $p < 0.05$; SP: $\beta = 0.18$, $p < 0.01$), providing support for H6a and H6b.

Test of mediation on purchase intention We estimated a mediation model based on 10,000 bootstrap samples (Hayes, 2018, PROCESS Model 4) with each of the three dimensions of product complexity as independent variables, expected product capability and usability as mediators, and purchase intention as the dependent variable. Moreover, we controlled for potential effects of age, gender, educational level, and consumer expertise. Consistent with the results related to H1a and H1b, we found no indirect effect of feature heterogeneity through capability (SH: $b = -0.17$; 95% CI = [−0.35 to 0.01]; SP: $b = 0.08$; 95% CI = [−0.13 to 0.30]), but we did observe a negative indirect effect through usability (SH: $b = -0.03$; 95% CI = [−0.08 to −0.00]; SP: $b = -0.07$; 95% CI = [−0.14 to −0.01]), as well as a partially significant, negative total effect (SH: $b = -0.20$; 95% CI = [−0.40 to −0.01]; SP: $b = 0.02$; 95% CI = [−0.21 to 0.24]). Moreover, consistent with our results related to H2a and H2b, we found a positive indirect effect of interrelatedness through capability (SH: $b = 0.36$; 95% CI = [0.19 to 0.55]; SP: $b = 0.79$; 95% CI = [0.57 to 1.02]) and a negative indirect effect through usability (SH: $b = -0.05$; 95% CI = [−0.10 to −0.01]; SP: $b = -0.07$; 95% CI = [−0.15 to −0.02]), accompanied by a positive total effect (SH: $b = 0.31$; 95% CI = [0.12 to 0.52]; SP: $b = 0.71$; 95% CI = [0.49 to 0.95]). Finally, consistent with the results related to H3a and H3b, we found a positive indirect effect of feature number through capability (SH: $b = 0.29$; 95% CI = [0.11 to 0.47]; SP: $b = 0.60$; 95% CI = [0.38 to 0.83]) and a negative indirect effect through usability (SH: $b = -0.11$; 95% CI = [−0.20 to −0.03]; SP: $b = -0.22$; 95% CI = [−0.35 to −0.11]), together with a partially significant, positive total effect (SH: $b = 0.18$; 95% CI = [−0.04 to 0.39]; SP: $b = 0.38$; 95% CI = [0.13 to 0.64]).

To take into account the nature of the proposed interactions of feature heterogeneity and interrelatedness with feature number, we estimated a moderated mediation model (Hayes, 2018, PROCESS Model 7), with feature number as the independent variable, feature heterogeneity and interrelatedness as moderators, expected product capability and usability as mediators, and purchase intention as the dependent variable. Again, we controlled for potential effects of age, gender, educational level, and consumer expertise. Consistent with the results related to H4a and H5a, feature heterogeneity did not affect the mediation through capability (SH: index of moderated mediation = −0.14; 95% CI = [−0.52 to 0.23]; SP: index of moderated mediation = −0.18; 95% CI = [−0.62 to 0.24]), but it enhanced the negative effect of feature number on purchase intention through usability (SH: index of moderated mediation = −0.22; 95% CI = [−0.42 to −0.02]; SP: index of moderated mediation = −0.14; 95% CI = [−0.30 to −0.02]). In addition, consistent with our results related to H4b, feature interrelatedness enhanced the positive effect of feature number on purchase intention through capability (SH: index of moderated mediation = 0.45; 95% CI = [0.08 to 0.80]; SP: index of moderated mediation = 0.44; 95% CI = [0.00 to 0.88]). Moreover, consistent with our results related to H5b, feature interrelatedness reduced the negative effect of feature number on purchase intention through usability in the smart home context (SH: index of moderated mediation = 0.20; 95% CI = [0.03 to 0.38]), but it increased the latter effect in the smartphone context (SP: index of moderated mediation = −0.11; 95% CI = [−0.25 to −0.01]).

Test of mediation on other downstream variables To validate our previous findings, we reestimated the mediation and moderated mediation models with other downstream variables.

First, following Thompson et al. (2005), we used product utility as the dependent variable and found the same pattern of effects as with product purchase intention (see Appendix 3, part C4). Second, we aimed to verify whether feature heterogeneity and interrelatedness combined with feature number also have a downstream effect on product purchase behavior. Therefore, at the end of the smartphone study, we entered participants in a lottery and asked them the following on a 7-point scale (1 = "another smartphone," 7 = "the described smartphone"): "If you are among the winners of our lottery, for which smartphone may we send you a discount voucher for purchase?" We assumed that the more participants tended toward "the described smartphone," the more favorable their purchase behavior related to this smartphone would be. The results showed the same pattern of effects as with product purchase intention (see Appendix 3, part C4).

Discussion

Studies 2a and 2b replicated the findings of Studies 1a and 1b by showing that feature heterogeneity and interrelatedness have discrete and somewhat different impacts on consumer attitudes. Specifically, the results confirmed that both dimensions decrease expected product usability whereas only interrelatedness increases expected product capability. We again tested whether consumers' lack of trust in products offered to them with a high dissimilarity of features could help explain our finding that feature heterogeneity does not increase expected product capability. The results of a mediation model based on 10,000 bootstrap samples (Hayes, 2018, PROCESS Model 4) again provide support for this explanation by showing that heterogeneity decreases consumers' product trust and, in turn, expected product capability (indirect effect: $b = -0.20$, $SE\,(\text{boot}) = 0.10$, 95% $CI = [-0.39; -0.01]$). More important, studies 2a and 2b revealed that not only feature number (see Thompson et al., 2005) but also feature heterogeneity and interrelatedness have downstream effects on consumer intentions and that these novel dimensions both also affect the corresponding impact of feature number. Table 1 summarizes the findings of the studies. It shows largely consistent findings across all studies and some noteworthy patterns of effects, which we subsequently discuss in more detail.

General discussion

Theoretical contributions

Previous research on consumer perceptions of complex products has mostly ignored dimensions other than number of features. This research represents the first investigation of how consumers perceive products across multiple dimensions of complexity. It makes three key contributions to research on new product design, advertising, and selling.

More comprehensive understanding of product complexity management By considering two additional dimensions of product complexity, our research enables marketing researchers to more comprehensively analyze the design of products and its impact on consumer perceptions and to derive more differentiated insights into the optimal advertising and selling of products. Moreover, it complements previous research on complex products in an R&D and manufacturing context (e.g., Ethiraj & Levinthal, 2004; Song et al., 2015) by revealing that the heterogeneity and interrelatedness of features have not only internal downstream effects on processes and costs but also external effects on consumer perceptions. In doing so, it contributes to a more holistic approach to product complexity management that considers both internal and external downstream effects of multiple complexity dimensions.

Thorough understanding of the impact of the various dimensions of product complexity By providing evidence that feature heterogeneity and interrelatedness influence consumer attitudes and intentions, we extend research on consumer perceptions of complex products, which so far has focused on the impact of feature number (Goodman & Irmak, 2013; Sela & Berger, 2012; Thompson & Norton, 2011; Thompson et al., 2005). Recent advancements in manufacturing, electronics, and information technology and the resulting increase in companies' ability and tendency to rely on highly heterogeneous and interrelated product features make this theoretical insight even more important. We also show that the two additional dimensions have both similarities and differences in how they affect consumer attitudes and intentions. In terms of similarities, both dimensions decrease expected product usability and, in turn, consumer purchase intention. In terms of differences, feature interrelatedness enhances expected product capability and, in turn, consumer purchase intention, while feature heterogeneity does not, potentially because of a lack of consumer trust in products with a high dissimilarity of features. In a pre-usage context, consumers are typically unable and at least partly unwilling to test a broad range of different product features, such that doubts about the product's ability to perform all these functions are likely to prevail. Because Thompson et al. (2005) examine the impact of feature number on the same dependent variables, a comparison of our findings with theirs is particularly necessary. We found that in terms of expected product usability, both feature interrelatedness and heterogeneity showed similar effects to those of feature number. By contrast, in terms of expected product capability, feature interrelatedness had a similar effect, but feature heterogeneity did not. Thus, in contrast with the quantity of features,

Table 1 Summary of results of hypotheses testing across studies

Hypotheses	Studies 1a (SH)/1b (SP) (2×2 design)	Studies 2a (SH)/2b (SP) (2×2×2 design)
H1: The heterogeneity of product features …		
(a) increases expected product capability.	a) – / –	a) – / –
(b) decreases expected product usability.	b) ✓ / ✓	b) ✓ / ✓
H2: The interrelatedness of product features …		
(a) increases expected product capability.	a) ✓ / ✓	a) ✓ / ✓
(b) decreases expected product usability.	b) ✓ / ✓	b) ✓ / ✓
H3: The number of product features …		
(a) increases expected product capability.		a) ✓ / ✓
(b) decreases expected product usability.		b) ✓ / ✓
H4: When the heterogeneity of product features is high rather than low, the number of product features …		
(a) increases expected product capability more strongly.		a) – / –
(b) decreases expected product usability more strongly.		b) ✓ / ✓
H5: When the interrelatedness of product features is high rather than low, the number of product features …		
(a) increases expected product capability more strongly.		a) ✓ / ✓
(b) decreases expected product usability more strongly.		b) – / ✓
H6: Product purchase intention in increased by …		
(a) expected product capability.		a) ✓ / ✓
(b) expected product usability.		b) ✓ / ✓

✓ confirmed; – not confirmed; *SH* smart home, *SP* smartphone

consumers do not seem to use the dissimilarity of features as an indicator of a product's ability to perform desired tasks.

Moreover, the external downstream effects of feature heterogeneity and interrelatedness on consumer perceptions tend to differ in valence from the internal downstream effects of these dimensions on internal processes and costs. For example, studies on product modularization argue that complex products should consist of modules as subsystems that highly differ in their functional properties and show minimal interdependence, which allows development and production of a large variety of products at lower costs and change of the product architecture without loss of functionality or performance (e.g., Bonvoisin et al., 2016; Campagnolo & Camuffo, 2010). Therefore, while the heterogeneity of a product's subsystems tends to have positive internal downstream effects and interrelatedness negative ones, our research indicates an opposite pattern for external downstream effects and, thus, a potential trade-off between internal and external consequences of these dimensions of product complexity.

In addition, our findings contribute to research on solution offerings that bundle products and services, or both, to solve customer problems (e.g., Kindström & Kowalkowski, 2009; Nordin & Kowalkowski, 2010; Windahl & Lakemond, 2010). Studies in this field frequently refer to the high complexity of these offerings (Kreye, 2019; Zou et al., 2018). Our findings suggest that broadening the range of these offerings is likely to lead to adverse consequences on the customer side whereas linking together the individual elements of the bundle can create additional functions that help solve customer problems.

Detailed understanding of the interplay between the various dimensions of product complexity By revealing that both feature heterogeneity and interrelatedness moderate the external downstream effects of feature number, our research shows that depending on these dimensions, the same feature number can lead to considerably different consumer reactions. While feature heterogeneity solely strengthens the usability-decreasing effect of feature number, feature interrelatedness primarily strengthens the capability-increasing effect of feature number. In this context, a particularly notable result relates to the mixed moderating impact of feature interrelatedness on the negative effect of feature number on expected product usability: in the smartphone context, the usability-decreasing effect of feature number is especially strong when feature interrelatedness is high; by contrast, in the smart home context, this effect is especially strong when feature interrelatedness is low. In a smartphone context, to establish a connection consumers must typically select and link each interrelated feature with other interrelated features manually (e.g., "camera" followed by "SMS" to send a picture). Thus, when the features of a smartphone are highly interrelated, an increasing number of features and, thus, connections between features require more additional decision and usage effort than when the features are less interrelated. By contrast, in a smart home context, consumers are typically able to create predefined processes (so-called automations) that enable them to regularly execute connected features in an automatic way. Thus, when the features of a smart home are highly interrelated, consumers are able to include a large share of features into predefined processes that allow them to automatically execute a series of connected features when using the product (e.g., “television” in combination with “multiroom audio” and “blinds” going down). Therefore, when the interrelatedness of smart home features is high, an increasing number of features and, thus, connections between features require less additional decision and usage effort than when the interrelatedness of smart home features is low and, thus, few features can be integrated into predefined processes and many features must be manually executed. Consequently, the direction of the moderating impact of feature interrelatedness seems to depend on a product’s degree of automation. When the degree of automation is rather low, feature interrelatedness tends to increase the negative effect of feature number on expected product usability, whereas when the degree of automation is rather high, it tends to decrease the corresponding effect.

Practical implications

This research offers recommendations on how best to manage the complexity of products across different stages of the innovation process, thereby maximizing the probability of new product success rather than failure and elimination (Cooper, 1979; Prigge et al., 2018). It provides guidance on product design (i.e., how to configure the various complexity dimensions) before market launch, and after market launch, it offers advice on product advertising and selling (i.e., which messaging about these dimensions to send to target groups).

Adopting a broader perspective on product complexity management Managers need to understand that consumers care not only about a product’s pure number of features but also about their functional dissimilarity and interdependence. Thus, these characteristics are relevant for both R&D and manufacturing and marketing. Therefore, when designing products managers should care not only about consequences for internal processes and costs but also about consequences for consumer perceptions. For modular product architectures, this advice may be particularly important because, in this context, modules as key structural elements should highly differ in their functional properties and not be interdependent from other modules to optimize the consequences of product design. By contrast, our findings show that this product design would lead to adverse consequences on the customer side. Thus, in this context, managers may need to trade off between internal and external consequences of these product complexity dimensions, for example, by relying on standardized interfaces between the structural elements, which allows mitigation of negative effects on internal processes and costs while ensuring high connectivity of these elements and, thus, enhanced functionality for consumers.

Moreover, to gain the maximum from a given number of features managers should simultaneously consider the heterogeneity and interrelatedness of these features when designing, advertising, and selling products. For example, by limiting actual or perceived feature heterogeneity and interrelatedness, they may lower the risk that consumers will expect a feature-rich product to be difficult to learn and use. Moreover, by fostering actual or perceived feature interrelatedness, they can help exploit the potential of a feature-rich new product to foster consumer beliefs about the product’s capability. Conversely, managers should consider a product’s number of features when deciding on the heterogeneity and interrelatedness of these features. We show that when the product is equipped with only a few features, managers can afford to rely on high feature heterogeneity. By contrast, particularly for a feature-rich product, managers should ensure that features are interrelated.

Promoting functional connectivity of features Rather than simply adding new features, and thus continuing the ongoing trend toward feature creep, managers could emphasize the interrelatedness of features. Specifically, when designing products, we advise to consider the functional connectivity of features an important criterion for the selection of features. These connections should not only be technically possible but also be easily buildable and capable of providing actual value for consumers. When creating manuals for products with high feature interrelatedness, it is important to include clear instructions on which features can be linked, how this can be done, and what benefits result from these connections. Moreover, when advertising and selling products, managers should highlight the functional connectivity of features and demonstrate the ease of use and associated benefits for consumers. For example, in commercials, print media, brochures, and websites, the interrelatedness of features could be illustrated by connecting lines between feature-related symbols. In this context, as well as in consultative and sales meetings, selected interrelated features and their ease of use and resulting benefits could also be highlighted and demonstrated to consumers.

Downplaying functional dissimilarity of features. Instead of constantly broadening the functional range of features to offer an “all-in-one” solution for every purpose, managers should rather deemphasize the dissimilarity of features.

Specifically, they could frame a product as offering complementary features for a similar overall purpose. For example, rather than highlighting that a smart home system controls both housing and lifestyle technology, they could emphasize the product's overarching purpose of smart home control, which makes the features appear more homogeneous. Moreover, particularly for products with high feature heterogeneity, managers may more strongly try to build trust, for example, by providing credible information about the product's capability, such as consumer reviews about subjective user experiences or third-party reviews about the results of objective product tests.

Solving the capability–usability trade-off through user-friendly design Finally, though not directly following from the findings of our research as the previous recommendations did, we recommend that rather than purely relying on weighing increased product capability with decreased product usability, or vice versa, managers could also try to relieve the tension between these competing consumer needs. To this end, a viable approach could be to develop more user-friendly product designs, such as through user surfaces that are more intuitive and better handling and decision support based on artificial intelligence.

Limitations and avenues for further research

This article has several limitations that offer avenues for further research. First, our study investigated the impact of various dimensions of product complexity on consumer attitudes and intentions before they actually use the product. Future studies might examine consumer reactions to product complexity during or after product usage to provide further nuance to our findings. Second, literature on information load suggests an inverted U-shaped effect of product information on consumer attitudes and intentions (Eppler & Mengis, 2004; Roetzel, 2019). However, our theoretical reasoning for the hypotheses draws on the implicit assumption that consumers already have a fair amount of information and thus focuses on the negative slope section from this literature. Future research could examine whether our findings hold in situations when consumers have only a limited amount of information. Alternatively, because our data do not allow us to test for quadratic effects, future research could also investigate the prevalence of an inverted U-shaped effect. Third, our study controlled for potential effects of demographics and psychographics. Further research could investigate these and other consumer characteristics, such as brand knowledge, product category knowledge, and product involvement as potential moderators. Fourth, we concentrated on smart home systems and smartphones as product categories. Additional research would benefit from transferring our conceptualization to other product categories. In this context, examining differences between products with a high versus low degree of automation would be particularly fruitful. Fifth, we focused on consumers. Further studies could extend this investigation to business customers. Sixth, to examine the impact of our findings on actual product purchase, future research could run a field experiment or analyze secondary data.

Appendix 1

Details on development of stimuli

Stimuli for heterogeneity of product features

To validate the operationalization of the heterogeneity of features, we drew on Blau's (1977) index of heterogeneity (B) using the formula $B = 1 - \sum p_i^2$, with p_i as the proportion of features belonging to the functional category i. This index describes the probability that two randomly selected features belong to different functional categories. Its minimum value $B_{\min}$ is 0, and its maximum value B_{max} can be calculated with the formula $B_{max} = (x - 1)/x$, where x refers to the quantity of functional categories. Thus, when features can belong to three functional categories, such as in our research, the value range of this index is between 0 and 0.67. For our "low heterogeneity of features" condition, we obtained $B = 0$ for the smart home and smartphone contexts, and for our "high heterogeneity of features" condition, we found B values between 0.64 and 0.67 for both product contexts (see parts A1 and B1 of the Supplemental Material). These results provide evidence for the appropriateness of our low/high classification in this dimension of product complexity.

Stimuli for interrelatedness of product features

To calculate the maximum quantity of connections between features c_{max} for the three conditions of number of product features, we applied the binomial coefficient "n choose 2" and the related formula $c_{max} = n(n-1)/2$ (Goetgheluck, 1987; Wasserman & Faust, 1994), where n is the number of features. Using this logic leads to $5(5-1)/2 = 10$ maximum connections for the "low number of features" condition, $10(10-9)/2 = 45$ maximum connections for the "medium number of features" condition, and $15(15-14)/2 = 105$ maximum connections for the "high number of features" condition.

To discount the proportion value pc_i for the "high number of features" condition by the factor 2 compared with the "low number of features" condition, we relied for "low number of features" on $pc_i = 0.10$ for "low interrelatedness of features," thus using 1 connection (i.e., $c = pc_i * c_{max} = 0.10 * 10 = 1$), and $pc_i = 0.50$ for "high interrelatedness of features," thus using 5 connections (i.e., $c = pc_i * c_{max} = 0.50 * 10 = 5$). By contrast, for "high number of features," we applied $pc_i = 0.05$ for "low interrelatedness of features," resulting in 5 connections (i.e., $c = pc_i * c_{max} = 0.05 * 105 = 5$), and $pc_i = 0.25$ for "high interrelatedness of features," leading to 26 connections (i.e., $c = pc_i * c_{max} = 0.25 * 105 = 26$). Similarly, for a medium number of features, we used the average between the proportion value pc_i of the "low number of features" condition and the "high number of features" condition. Thus, we relied on $pc_i = 0.075$ for "low interrelatedness of features," obtaining 3 connections (i.e., $c = pc_i * c_{max} = 0.075 * 45 = 3$), and $pc_i = 0.375$ for "high interrelatedness of features," resulting in 17 connections (i.e., $c = pc_i * c_{max} = 0.375 * 45 = 17$) (see parts A2 and B2 of the Supplemental Material).

Appendix 2

Details on studies 1a and 1b

Details on pretest for studies 1a and 1b

To ensure the suitability of our manipulations and rule out confounding effects, we carried out comprehensive pretests of stimuli with consumers in the smart home (SH) and smartphone (SP) contexts (SH: $n = 75$; 48% female, $M_{age} = 47.69$ years; SP: $n = 77$; 47% female, $M_{age} = 45.87$ years). We used two 2×2 analyses of variance (ANOVAs) with heterogeneity and interrelatedness of features as independent variables and the two manipulation check questions as dependent variables, respectively, while holding the number of features constant on a medium level. We applied 7-point scales for all questions. As expected, for the manipulation check question for the heterogeneity of features ("This [smart home system; smartphone] consists of features of the same category vs. features of different categories") as the dependent variable, the analysis showed only a significant effect for heterogeneity of features (SH: $M_{low\ hete} = 4.94$, $SD = 1.89$ vs. $M_{high\ hete} = 5.87$, $SD = 1.32$; $F(1, 71) = 5.86$, $p < 0.05$; SP: $M_{low\ hete} = 3.64$, $SD = 1.67$ vs. $M_{high\ hete} = 5.06$, $SD = 1.64$; $F(1, 73) = 13.88$, $p < 0.01$), but neither the effect of interrelatedness nor the interaction was significant. Similarly, for the manipulation check question for the interrelatedness of features as the dependent variable ("This [smart home system; smartphone] shows a low degree of functional connectivity vs. a high degree of functional connectivity"), only interrelatedness of features showed a significant effect (SH: $M_{low\ inter} = 3.77$, $SD = 1.94$ vs. $M_{high\ inter} = 5.93$, $SD = 1.09$; $F(1, 71) = 36.62$, $p < 0.01$; SP: $M_{low\ inter} = 3.23$, $SD = 1.73$ vs. $M_{high\ inter} = 5.71$, $SD = 1.20$; $F(1, 73) = 51.13$, $p < 0.01$), but neither the effect of heterogeneity nor the interaction was significant. Thus, all manipulations worked as intended. In addition, we analyzed whether participants perceived the products as equal in terms of number of features and found no significant differences among the four scenarios (SH: $F(1, 71) = 2.64$, $p = 0.06$; SP: $F(1, 73) = 1.88$, $p = 0.14$).

We also pretested whether the two dimensions empirically differ from each other. For this purpose, we presented participants with two products with the same number of features. The products differed only in the heterogeneity and interrelatedness of features, such that one was low in heterogeneity but high in interrelatedness and the other was high in heterogeneity but low in interrelatedness. We asked participants to rate the systems/smartphones on a 7-point scale (1 = "The smart home systems/smartphones are identical," 7 = "The smart home systems/smartphones are different from each other") and found that they rated the two products as very different (SH: $M = 6.57$; SP: $M = 6.40$).

Details on measures of studies 1a and 1b

We measured consumer expertise with five items (e.g., "How familiar are you with [smart home systems; smartphones]?" "not familiar at all/extremely familiar"; SH: $\alpha = 0.91$; SP: $\alpha = 0.90$; Thompson et al., 2005), consumer trust with three items (e.g., "I expect this [smart home system; smartphone] to deliver on its promise"; SH: $\alpha = 0.91$; Li et al., 2008), expected product capability with three items (e.g., "This [smart home system; smartphone] will perform well"; SH: $\alpha = 0.97$; SP: $\alpha = 0.95$), and expected product usability with eight items (e.g., "Learning to use this [smart home system; smartphone] will be easy for me"; SH: $\alpha = 0.97$; SP: $\alpha = 0.96$). Part D of the Supplemental Material shows the complete items for each scale.

Details on manipulation checks for studies 1a and 1b

Similar to our pretests of manipulations, for both Studies 1a and 1b, we used a 2×2 ANOVA with heterogeneity and interrelatedness of features as independent variables and the two manipulation check questions as dependent variables, respectively. For the manipulation check question related to heterogeneity of features, the results showed only a significant effect of heterogeneity (SH: $M_{low\ hete} = 4.54$, $SD = 2.01$ vs. $M_{high\ hete} = 5.65$, $SD = 1.66$; $F(1, 236) = 21.50$, $p < 0.01$; SP: $M_{low\ hete} = 3.71$, $SD = 1.92$ vs. $M_{high\ hete} = 5.02$, $SD = 1.29$; $F(1, 191) = 28.78$, $p < 0.01$). By contrast, the effect of interrelatedness and the interaction did not reach significance. For the manipulation check question related to interrelatedness of features, only interrelatedness had a significant effect in the smart home context (SH: $M_{low\ inter} = 3.42$, $SD = 1.83$ vs. $M_{high\ inter} = 5.72$, $SD = 1.51$; $F(1, 236) = 111.93$, $p < 0.01$); neither the effect of heterogeneity nor the interaction was significant. In the smartphone context, we observed a significant main effect of not only interrelatedness (SP: $M_{low\ inter}=3.01$, $SD=1.58$ vs. $M_{high\ inter}=5.17$, $SD=1.28$; $F(1, 191)=108.86$, $p<0.01$) but also heterogeneity ($F(1, 191)=6.76$, $p<0.05$), while the interaction was not significant ($F(1, 191)=0.14$, $p=0.71$). Given the significant effect of heterogeneity, we followed the common advice (Perdue & Summers, 1986) and practice (Bellezza et al., 2014; Sipilä et al., 2021) to compare effect sizes of all significant effects. Perdue and Summers (1986, p. 323) recommended that "when in the analysis of the manipulation check for A the effects sizes for B [and AB] … are much smaller than that for A, their statistical significance probably should not be of great concern". In our study, we found that for the manipulation check question related to interrelatedness of features, the effect size of interrelatedness ($\eta^2=0.36$) was 12 times higher than that of heterogeneity ($\eta^2=0.03$), providing sufficient support for our manipulation. Therefore, and following the suggestion of Sawyer et al., (1995, p. 592) that manipulation and confounding checks add less informational value "when … the independent variables are isomorphic with their operationalization," such as in our study, we relied on the corresponding stimuli.

Appendix 3

Details on studies 2a and 2b

Details on pretest for studies 2a and 2b

As in Studies 1a and 1b, we conducted comprehensive pretests of our stimuli with consumers in both smart home (SH) and smartphone (SP) contexts (SH: $n=112$; 51% female, $M_{age}=43.72$ years; SP: $n=73$; 40% female, $M_{age}=45.05$ years). We used two $2\times2\times2$ ANOVAs with number, heterogeneity, and interrelatedness of features as independent variables and the three manipulation check questions as dependent variables. Again, we applied 7-point scales for all questions. As expected, for the manipulation check question with the number of product features ("This [smart home system; smartphone] has a low number of features vs. a high number of features") as the dependent variable, the results showed only a significant effect for number of product features (SH: $M_{low\ num}=3.86$, $SD=1.84$ vs. $M_{high\ num}=5.99$, $SD=1.32$; $F(1, 104)=46.00$, $p<0.01$; SP: $M_{low\ num}=3.42$, $SD=1.82$ vs. $M_{high\ num}=5.36$, $SD=1.46$; $F(1, 65)=25.27$, $p<0.01$), while no other effects were significant. For heterogeneity of product features, we used the same manipulation check question as in Studies 1a and 1b and found support for a successful manipulation (SH: $M_{low\ hete}=3.75$, $SD=1.63$ vs. $M_{high\ hete}=5.18$, $SD=1.55$; $F(1, 104)=22.19$, $p<0.01$; SP: $M_{low\ hete}=3.40$, $SD=1.99$ vs. $M_{high\ hete}=4.61$, $SD=1.59$; $F(1, 65)=7.28$, $p<0.05$), while no other effects reached significance. Similarly, for interrelatedness of product features we used the same manipulation check question as in Studies 1a and 1b. The results showed a significant effect for interrelatedness of product features (SH: $M_{low\ inter}=3.32$, $SD=2.03$ vs. $M_{high\ inter}=5.03$, $SD=1.81$; $F(1, 104)=22.11$, $p<0.01$; SP: $M_{low\ inter}=3.33$, $SD=1.84$ vs. $M_{high\ inter}=4.94$, $SD=1.67$; $F(1, 65)=15.84$, $p<0.01$), while no other effects were significant. Thus, all manipulations worked as intended.

Details on measures of studies 2a and 2b

We used the same scales for measuring consumer expertise (SH: $\alpha=0.90$; SP: $\alpha=0.90$), consumer trust (SH: $\alpha=0.91$), expected product capability (SH: $\alpha=0.96$; SP: $\alpha=0.96$), and expected product usability (SH: $\alpha=0.97$; SP: $\alpha=0.96$). In addition, we measured product purchase intention with three items from Dodds et al. (1991) on a 7-point scale (1 = "strongly disagree," 7 = "strongly agree") (e.g., "My willingness to buy this [smart home system; smartphone] is very high"; SH: $\alpha=0.98$; SP: $\alpha=0.98$). In part D of the Supplemental Material, we show the complete items for each scale.

Details on manipulation checks for studies 2a and 2b

As in our pretests of manipulations, for both Studies 2a and 2b, we used a $2\times2\times2$ ANOVA with number, heterogeneity, and interrelatedness of features as independent variables and the three manipulation check questions as the respective dependent variables. For the manipulation check question related to number of features, we observed a significant effect of not only number (SH: $M_{low\ num}=3.33$, $SD=1.96$ vs. $M_{high\ num}=6.03$, $SD=1.50$; $F(1, 431)=276.67$, $p<0.01$; SP: $M_{low\ num}=3.08$, $SD=1.74$ vs. $M_{high\ num}=5.50$, $SD=1.54$; $F(1, 441)=254.87$, $p<0.01$) but also interrelatedness (SH: $F(1, 431)=23.77$, $p<0.01$; SP: $F(1, 441)=24.04$, $p<0.01$). Given the significant effect of interrelatedness, we followed common recommendations (Perdue & Summers, 1986) and practices (Bellezza et al., 2014; Sipilä et al., 2021) to compare effect sizes. The size of the focal effect of number (SH: $\eta^2=0.39$; SP: $\eta^2=0.37$) was significantly higher than the effect of interrelatedness (SH: $\eta^2=0.05$; SP: $\eta^2=0.05$), providing sufficient support for our manipulation. For the manipulation check question related to heterogeneity of features, the results showed a strong, significant effect of heterogeneity (SH: $M_{low\ hete}=3.70$, $SD=2.26$ vs. $M_{high\ hete}=5.73$, $SD=1.57$; $F(1, 431)=130.28$, $p<0.01$, $\eta^2=0.23$; SP: $M_{low\ hete}=3.82$, $SD=1.85$ vs. $M_{high\ hete}=5.00$, $SD=1.71$; $F(1, 441)=51.01$, $p<0.01$, $\eta^2=0.10$). We also found a weak, significant effect of number (SH: $F(1, 431)=22.38$, $p<0.01$, $\eta^2=0.05$; SP: $F(1, 441)=22.58$, $p<0.01$, $\eta^2=0.05$) and, at least for one product context, of interrelatedness

(SH: $F(1, 431) = 10.40$, $p < 0.01$, $\eta^2 = 0.02$). The size of the focal effect of heterogeneity was significantly higher in all cases, providing sufficient support for our manipulation (Bellezza et al., 2014; Perdue & Summers, 1986; Sipilä et al., 2021). Finally, for the manipulation check question related to interrelatedness, we found a strong, significant effect of interrelatedness (SH: $M_{low\ inter} = 3.05$, $SD = 1.87$ vs. $M_{high\ inter} = 5.52$, $SD = 1.72$; $F(1, 431) = 232.92$, $p < 0.01$, $\eta^2 = 0.35$; SP: $M_{low\ inter} = 3.08$, $SD = 1.79$ vs. $M_{high\ inter} = 5.15$, $SD = 1.48$; $F(1, 441) = 195.85$, $p < 0.01$, $\eta^2 = 0.31$); the results also showed a weak, significant effect of number (SH: $F(1, 431) = 49.60$, $p < 0.01$, $\eta^2 = 0.10$; SP: $F(1, 441) = 54.47$, $p < 0.01$, $\eta^2 = 0.11$). Again, we compared effect sizes and found that the size of the focal effect of interrelatedness was significantly higher in all cases, providing sufficient support for our manipulation (Bellezza et al., 2014; Perdue & Summers, 1986; Sipilä et al., 2021). Therefore, and again considering the suggestion of Sawyer et al. (1995) that manipulation and confounding checks have less informational value when the independent variables of an experiment are isomorphic with their operationalization, such as in our study, we drew on the corresponding stimuli.

Details on results (tests of mediation on other downstream variables)

Test of mediation on expected product utility For validation purposes, we estimated a mediation model based on 10,000 bootstrap samples (Hayes, 2018, PROCESS Model 4) with each of the three dimensions of product complexity as independent variables, expected capability and usability as mediators, and expected product utility as the dependent variable. We measured expected product utility on a 7-point semantic differential scale with the same items that Thompson et al. (2005) use ("Please evaluate this [smart home system; smartphone] by the following characteristics: bad vs. good; unlikeable vs. likeable; not useful vs. useful; low quality vs. high quality; undesirable vs. desirable; unfavorable vs. favorable"; SH: $\alpha = 0.97$; SP: $\alpha = 0.97$). In line with the results related to purchase intention as the dependent variable, we found a significant indirect effect of feature heterogeneity not through capability (SH: $b = -0.21$; 95% CI = [−0.43 to 0.01]; SP: $b = 0.08$; 95% CI = [−0.12 to 0.29]) but through usability (SH: $b = -0.05$; 95% CI = [−0.11 to −0.00]; SP: $b = -0.05$; 95% CI = [−0.11 to −0.01]). Moreover, also in line with the results related to purchase intention as the dependent variable, we found a significant indirect effect of feature interrelatedness through capability (SH: $b = 0.46$; 95% CI = [0.24 to 0.69]; SP: $b = 0.76$; 95% CI = [0.56 to 0.98]) and usability (SH: $b = -0.08$; 95% CI = [−0.14 to −0.03]; SP: $b = -0.06$; 95% CI = [−0.11 to −0.01]). In addition, the results indicated significant indirect effects of feature number through capability (SH: $b = 0.36$; 95% CI = [0.13 to 0.59]; SP: $b = 0.58$; 95% CI = [0.37 to 0.80]) and usability (SH: $b = -0.17$; 95% CI = [−0.26 to −0.09]; SP: $b = -0.17$; 95% CI = [−0.26 to −0.09]), confirming our mediation findings related to purchase intention as the dependent variable.

Test of moderated mediation on expected product utility We also ran a moderated mediation model (Hayes, 2018, PROCESS Model 7) with feature number as the independent variable, feature heterogeneity and interrelatedness as moderators, expected capability and usability as mediators, and expected product utility as the dependent variable. For feature heterogeneity, we found a significant moderated mediation not through capability (SH: index of moderated mediation = −0.17; 95% CI = [−0.65 to 0.30]; SP: index of moderated mediation = −0.17; 95% CI = [−0.59 to 0.23]) but through usability (SH: index of moderated mediation = −0.28; 95% CI = [−0.54 to −0.03]; SP: index of moderated mediation = −0.11; 95% CI = [−0.24 to −0.02]). For feature interrelatedness, our results indicate a significant moderated mediation through capability (SH: index of moderated mediation = 0.57; 95% CI = [0.10 to 1.04]; SP: index of moderated mediation = 0.43; 95% CI = [0.00 to 0.85]) and usability (SH: index of moderated mediation = 0.27; 95% CI = [0.04 to 0.52]; SP: index of moderated mediation = −0.08; 95% CI = [−0.18 to −0.00]). In summary, these findings are fully consistent with our mediated moderation findings related to purchase intention as the dependent variable.

Test of mediation on product purchase behavior We conducted mediation analysis based on 10,000 bootstrap samples (Hayes, 2018, PROCESS Model 4) with each of the three dimensions of product complexity as independent variables, expected capability and expected usability as mediators, and product purchase behavior as the dependent variable. Consistent with our other findings, we found a significant indirect effect of heterogeneity of features not through capability ($b = 0.05$; 95% CI = [−0.08 to 0.19]) but through usability ($b = -0.06$; 95% CI = [−0.12 to −0.01]). Furthermore, in line with our previous findings, we found a significant indirect effect of feature interrelatedness through capability ($b = 0.48$; 95% CI = [0.32 to 0.66]) and usability ($b = -0.06$; 95% CI = [−0.14 to −0.01]) as well as of feature number through capability ($b = 0.36$; 95% CI = [0.22 to 0.54]) and usability ($b = -0.17$; 95% CI = [−0.31 to −0.05]).

Test of moderated mediation on product purchase behavior We estimated a moderated mediation model (Hayes, 2018, PROCESS Model 7) with feature number as the independent variable, feature heterogeneity and interrelatedness as moderators, expected capability and usability as mediators, and product purchase behavior as the dependent variable. For feature heterogeneity, we found a significant moderated mediation not through capability (index of moderated mediation = −0.11; 95% CI = [−0.38 to 0.15]) but through usability (index of moderated mediation = −0.11; 95% CI = [−0.25 to −0.01]). For feature interrelatedness, our results show a significant moderated mediation through capability (index of moderated mediation = 0.27; 95% CI = [0.00 to 0.56]) and usability (index of moderated mediation = −0.08; 95% CI = [−0.21 to −0.00]). Overall, these findings are fully in line with our mediated moderation findings related to purchase intention as the dependent variable.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Achrol, R. S., & Stern, L. W. (1988). Environmental determinants of decision-making uncertainty in marketing channels. *Journal of Marketing Research, 25*(1), 36–50.

Bandyopadhyay, S., Rao, A. R., & Sinha, B. (2010). *Models for social networks with statistical applications*. SAGE.

Bellezza, S., Gino, F., & Keinan, A. (2014). The red sneakers effect: Inferring status and competence from signals of nonconformity. *Journal of Consumer Research, 41*(1), 35–54.

Bertini, M., Ofek, E., & Ariely, D. (2009). The impact of add-on features on consumer product evaluations. *Journal of Consumer Research, 36*(1), 17–28.

Bettencourt, L. A., & Bettencourt, S. L. (2011). Innovating on the cheap. *Harvard Business Review, 89*(6), 88–94.

Bettman, J., Johnson, E., & Payne, J. (1991). Consumer decision making. In T. Robertson & H. Kassarjian (Eds.), *Handbook of consumer behavior* (pp. 50–84). Prentice Hall.

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. Free Press.

Blut, M., Wang, Ch., & Schoefer, K. (2016). Factors influencing the acceptance of self-service technologies. *Journal of Service Research., 19*(4), 396–416.

Bonvoisin, J., Halstenberg, F., Buchert, T., & Stark, R. (2016). A systematic literature review on modular product design. *Journal of Engineering Design, 27*(7), 488–514.

Buescher, M., Slack, R., Rouncefield, M., Procter, R., Hartswood, M., & Voss, A. (2009). *Configuring user-designer relations*. Springer.

Campagnolo, D., & Camuffo, A. (2010). The concept of modularity in management studies: A literature review. *International Journal of Management Reviews, 12*(3), 259–283.

Chang, Y., Dong, X., & Sun, W. (2014). Influence of characteristics of the Internet of Things on consumer purchase intention. *Social Behavior and Personality, 42*(2), 321–330.

Cooper, R. G. (1979). The dimensions of industrial new product success and failure. *Journal of Marketing, 43*(3), 93–103.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

De Angelis, M., & Carpenter, G. S. (2009). The effect of adding features on product attractiveness: The role of product perceived congruity. In A. L. McGill & S. Shavitt (Eds.), *Advances in consumer research* (Vol. 36, pp. 651–652), Duluth, MN: Association for Consumer Research.

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research, 28*(3), 307–319.

Duncan, R. B. (1972). Characteristics of organizational environments and perceived environmental uncertainty. *Administrative Science Quarterly, 17*(3), 313–327.

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society, 20*(5), 325–344.

Estes, Z. (2003). A tale of two similarities: Comparison and integration in conceptual combination. *Cognitive Science, 27*, 911–921.

Ethiraj, S. K., & Levinthal, D. (2004). Modularity and innovation in complex systems. *Management Science, 50*(2), 159–173.

Fürst, A., & Scholl, M. (2022). Multi-channel management and design: An analysis of their impact on multi-channel conflict and success. *Marketing ZFP*, 44(3), 24–43.

Fürst, A., & Staritz, M. (2022). Creating superior value in the eyes of the customer: An analysis of the two value drivers and value paths. *Marketing ZFP, 44*(3), 3–23.

Gattol, V., Sääksjärvi, M., Gill, T., & Schoormans, J. (2016). Feature fit – The role of congruence and complementarity when adding versus deleting features from products. *European Journal of Innovation Management, 19*(4), 589–607.

Gibbert, M., & Mazursky, D. (2009). How successful would a phone-pillow be. *Journal of Consumer Psychology, 19*(4), 652–660.

Goetgheluck, P. (1987). Computing binomial coefficients. *American Mathematical Monthly, 94*(4), 360–365.

Goodman, J. K., & Irmak, C. (2013). Having versus consuming: Failure to estimate usage frequency makes consumers prefer multifeature products. *Journal of Marketing Research, 50*(1), 44–54.

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems, 29*(7), 1645–1660.

Gupta, A., Kumar, A., Grewal, R., & Lilien, G. L. (2019). Within-seller and buyer–seller network structures and key account profitability. *Journal of Marketing, 83*(1), 108–132.

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2d ed.). The Guilford Press.

Hoffman, D. L., & Novak, T. P. (2018). Consumer and object experience in the Internet of Things: An assemblage theory approach. *Journal of Consumer Research, 44*(6), 1178–1204.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology, 79*(6), 995–1006.

Ji, Y. G., Park, J., Lee, C., & Yun, M. (2006). A usability checklist for the usability evaluation of mobile phone user interface. *International Journal Human-Computer Interaction, 20*(3), 207–231.

Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. *Management Science, 31*(4), 395–414.

Kannan, P. K., & Li, H. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing, 34*(1), 22–45.

Kim, H.-W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems, 43*(1), 111–126.

Kindström, D., & Kowalkowski, C. (2009). Development of industrial service offerings: A process framework. *Journal of Service Management, 20*(2), 156–172.

Kreye, M. E. (2019). Does a more complex service offering increase uncertainty in operations? *International Journal of Operations & Production Management, 39*(1), 75–93.

Krishnan, H. S. (1996). Characteristics of memory associations: A consumer-based brand equity perspective. *International Journal of Research in Marketing, 13*(4), 389–405.

Kuehnl, Ch., Fürst, A., Homburg, Ch., & Staritz, M. (2017). Toward a differentiated understanding of the value-creation chain. *British Journal of Management, 28*(3), 444–463.

Lau, A. K. W., Yam, R. C. M., & Tang, E. (2011). The impact of product modularity on new product performance: Mediation by product innovativeness. *Journal of Product Innovation Management, 28*(2), 270–284.

Lee, J., & Chu, W. (2021). The effect of adding focal-goal similar versus dissimilar attributes on convergence product purchase decision: The role of relational and item-specific elaboration style. *Journal of Consumer Behaviour, 21*(2), 1–14.

Li, F., Kashyap, R., Zhou, N., & Yang, Z. (2008). Brand trust as a second-order factor: An alternative measurement model. *International Journal of Market Research, 50*(6), 817–839.

Meyer, R. J., Zhao, S., & Han, J. K. (2008). Biases in valuation vs. usage of innovative product features. *Marketing Science, 27*(6), 1083–1096.

Mukherjee, A., & Hoyer, W. D. (2001). The effect of novel attributes on product evaluation. *Journal of Consumer Research, 28*(3), 462–472.

Ng, I. C. L., & Wakenshaw, S. Y. L. (2017). The Internet-of-Things: Review and research directions. *International Journal of Research in Marketing, 34*(1), 3–21.

Nordin, F., & Kowalkowski, C. (2010). Solutions offerings: A critical review and reconceptualisation. *Journal of Service Management, 21*(4), 441–459.

Nowlis, S. M., & Simonson, I. (1996). The effect of new product features on brand choice. *Journal of Marketing Research, 33*(1), 36–46.

Nysveen, H., Pedersen, P. E., & Thorbjørnsen, H. (2005). Intentions to use mobile services: Antecedents and cross-service comparisons. *Journal of the Academy of Marketing Science, 33*(3), 330–346.

Payne, J. W. (1982). Contingent decision behavior. *Psychological Bulletin, 92*(2), 382–402.

Perdue, B. C., & Summers, J. O. (1986). Checking the success of manipulations in marketing experiments. *Journal of Marketing Research, 23*(4), 317–326.

Pinochet, L. H. C., Lopes, E. L., Srulzon, C. H. F., & Onusic, L. M. (2018). The influence of the attributes of "Internet of Things" products on functional and emotional experiences of purchase intention. *Innovation & Management Review, 15*(3), 303–320.

Preece, J., Rogers, Y., & Sharp, H. (2002). *Interaction design*. Wiley.

Prigge, J., Homburg, Ch., & Fürst, A. (2018). Addressing a product management's orphan: How to externally implement product eliminations in a B2B Setting. *Industrial Marketing Management, 68*(1), 56–73.

Raff, S., Wentzel, D., & Obwegeser, N. (2020). Smart products: Conceptual review, synthesis, and research directions. *Journal of Product Innovation Management, 37*(5), 379–404.

Roetzel, P. G. (2019). Information overload in the information age: A review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. *Business Research, 12*(2), 479–522.

Sääksjärvi, M., & Samiee, S. (2011). Assessing multifunctional innovation adoption via an integrative model. *Journal of the Academy of Marketing Science, 39*(5), 717–735.

Sawyer, A. G., Lynch, J. G., & Brinberg, D. L. (1995). A Bayesian analysis of the information value of manipulation and confounding checks in theory tests. *Journal of Consumer Research, 21*(4), 581–595.

Scott, J. (1988). Social network analysis. *Sociology, 22*(1), 109–127.

Sela, A., & Berger, J. (2012). How attribute quantity influences option choice. *Journal of Marketing Research, 49*(6), 942–953.

Shugan, S. M. (1980). The cost of thinking. *Journal of Consumer Research, 7*(2), 99–111.

Sipilä, J., Alavi, S., Edinger-Schons, L. M., Dörfer, S., & Schmitz, Ch. (2021). Corporate social responsibility in luxury contexts: Potential pitfalls and how to overcome them. *Journal of the Academy of Marketing Science, 49*(2), 280–303.

Song, W., Wu, Z., Li, X., & Xu, Z. (2015). Modularizing product extension services: An approach based on modified service blueprint and fuzzy graph. *Computers & Industrial Engineering, 85*, 186–195.

Thompson, D. V., Hamilton, R. W., & Rust, R. T. (2005). Feature fatigue: When product capabilities become too much of a good thing. *Journal of Marketing Research, 42*(4), 431–442.

Thompson, D. V., & Norton, M. I. (2011). The social utility of feature creep. *Journal of Marketing Research, 48*(3), 555–565.

Thompson, J. D. (1967). *Organizations in action*. McGraw-Hill.

Von Bertalanffy, L. (1968). *General system theory: Foundations, development, applications*. George Braziller.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge University Press.

Wilkenfeld, M. J., & Ward, T. B. (2001). Similarity and emergence in conceptual combination. *Journal of Memory and Language, 45*(1), 21–38.

Windahl, C., & Lakemond, N. (2010). Integrated solutions from a service-centered perspective: Applicability and limitations in the capital goods industry. *Industrial Marketing Management, 39*(8), 1278–1290.

Zou, W., Brax, S.A., & Rajala, R. (2018). Complexity and its dimensions in the servitization literature: a systematic review. Spring Servitization Conference, Copenhagen 14–16 May.