Computers in Human Behavior Reports 6 (2022) 100193

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

# Recommender system information trustworthiness: The role of perceived ability to learn, self-extension, and intelligence cues

Wojciech Trzebiński *, Beata Marciniak

*SGH Warsaw School of Economics, Collegium of Management and Finance, Poland*

A R T I C L E I N F O

*Keywords:*
Recommender systems
AI-based systems
Artificial intelligence
Ability to learn
Personalization
Consumer response
Information trustworthiness
Self-extension
Anthropomorphism

A B S T R A C T

Making consumers trust in product descriptions provided by recommender systems is important for marketers, managers, and IT developers dealing with AI-based recommenders. The previous related research has focused on the relationship between the personalization of a recommender system's offering and consumer trust in the system. This paper aims to extend this literature by investigating how the perceived recommender system ability to learn influences the perceived trustworthiness of the recommended product descriptions. Additionally, it is studied what role the consumer self-extension into system recommendations and intelligence cues play in this relationship. Two studies (Study 1 and Study 2) were conducted among young adults participating in an online research panel. Both studies used smartphones as a product category. All study participants were exposed to the same set of product descriptions ostensibly provided by recommender systems. Study 1 surveyed actual Facebook users ($N = 204$) and assumed Facebook as a recommender system. Perceived ability to learn, self-extension, and perceived trustworthiness were rated by the participants, and the measurements were analyzed with a mediation model. Perceived ability to learn had a positive effect on perceived description trustworthiness, and self-extension mediated this relationship. Study 2 ($N = 515$) was an experiment. The participants were exposed to a fictitious recommender system. Ability-to-learn cues (like asking about preferences; present vs. absent) and anthropomorphic cues (like first-person and conversation-like communication; present vs. absent) were manipulated between-subject. Perceived ability to learn, perceived anthropomorphism, and trustworthiness were rated by the participants, and the measurements were analyzed with ANOVA and moderated mediation models. Ability-to-learn cues × anthropomorphism cues interaction effect occurred on perceived ability to learn and trustworthiness. The positive effect of ability-to-learn cues on perceived ability to learn (perceived trustworthiness) was more positive (occurred only) in the presence of anthropomorphic cues. The paper extends the existing knowledge on consumer response to recommender systems by linking perceived system ability to learn and perceived recommended product description trustworthiness (with the evaluated offerings unchanged). Moreover, the paper provides novel insights into the role of self-extension and system intelligence cues in building consumer trust in recommender systems. The results may guide marketers, managers, IT developers, and policymakers dealing with AI-based systems through the possible consequences of developing AI technology in recommender systems.

## Introduction

AI-based recommender systems have become an integral part of modern business environments based on digital technologies (Araujo et al., 2020). Thus, those systems may have a profound impact on consumer behavior. The information systems are defined as tools supporting consumers in information search and interacting with them (Ariely, 2000). Such a system (or, more generally, a product) is intelligent if it can collect, process, and produce information (Rijsdijk et al., 2007), and its capabilities evolve through data being collected (Chouk & Mani, 2019). Intelligent recommender systems provide recommendations on what to buy (Häubl & Trifts, 2000, Klaus & Zaichkowsky, 2020; Komiak & Benbasat, 2006; Labecki et al., 2018; Xiao & Benbasat, 2007) that may be based on preference information explicitly given by target consumers or inferred by the system. Modern AI-based systems provide consumers with an already digested information stream (Wirtz et al., 2018), enabling them to outsource the decision-making process (Labecki et al., 2018). On the other hand, marketers can use such online communication

* Corresponding author.
*E-mail address:* wtrzebi@sgh.waw.pl (W. Trzebiński).

https://doi.org/10.1016/j.chbr.2022.100193
Received 10 January 2021; Received in revised form 14 March 2022; Accepted 30 March 2022
Available online 9 April 2022

to control the flow of product information reaching consumers (Swaminathan, 2003). Hence, the intelligence of recommender systems may be potentially used in favor or against consumers. Therefore, it is crucial how recommender system intelligence influences consumer trust in those systems.

The existing literature broadly addresses how the quality of actual product offerings proposed by recommender systems influence consumer response. Specifically, the previous related studies investigated the consequences of the actual personalization of offerings in consumer satisfaction and loyalty (Desai, 2019; Fan et al., 2020; Nguyen & Sidorova, 2018; Qiu & Benbasat, 2009; Sivaramakrishnan et al., 2007; Tyrväinen et al., 2020; Yoon et al., 2013), trust in a system (Abumalloh et al., 2020; Komiak & Benbasat, 2006), user experience (Chen et al., 2020), attitude toward ads and the presented offering (Gaber et al., 2019; Gao & Huang, 2019; Prentice et al., 2020; Rhee & Choi, 2020), user activity and engagement (Prentice et al., 2020, see Zanker et al., 2019 for review), brand identification (Tran et al., 2020), decision making quality and efficiency (references in Swaminathan, 2003; Xiao & Benbasat, 2007), and recommendation quality perception (Yoon et al., 2013).

Despite the above extent research effort, several significant gaps remain. First, those studies focused on the personalization of offerings proposed by recommendation systems rather than the systems' intelligence. Therefore, our study considers the recommender system ability to learn as a focal factor of consumer response to system offerings. The ability to learn is considered one of the product intelligence dimensions (Rijsdijk et al., 2007). Offering personalization may result from systems' ability to learn about their users, but those two constructs are far from equal. While the ability to learn is a property of a system itself, personalization is a property of the system's particular offering.

Second, the existing research on consumer response to recommender systems focuses on those systems' actual offerings. However, the *actual* personalization of an offering proposed by a system is distinct from the offering's *perceived* personalization (Li, 2016). Hence, the effects of *actual* characteristics of a personalized offering should be distinguished from the effects of the *perception* of a recommender system as able to learn (i.e., when an actual offering that is evaluated remains unchanged). Regarding those latter kinds of effects, it has been demonstrated that an offering believed to be personalized by a system is better evaluated by consumers (Hamilton et al., 2020), and it prompts impulsive purchase intentions (Zhang et al., 2020). When a system is described as learning a consumer, high-construal messages are more persuasive (Kim & Duhachek, 2018). However, to the best of our knowledge, no study directly investigated the effects of the perceived recommender system's ability to learn on consumer trust.

Third, the existing studies on recommender systems that pertain to consumer trust, like Komiak and Benbasat (2006), link personalization with consumer trust in a system. However, the trust in a recommender system is not equivalent to the perceived trustworthiness of recommended product descriptions provided by the system. While the former construct focuses on a system itself, the latter pertains to a particular offering recommended by the system and can be more directly connected with behavioral outcomes related to this offering.

Those gaps are meaningful theoretically, but they also represent crucial dilemmas of marketers, managers, and IT developers dealing with recommender systems. Namely, the issue of building consumer trust in product descriptions provided by recommender systems may be addressed not only through better quality of particular recommendations but also by designing the system and building the relationship with users, which may shape their perception of the system's intelligence. To address those gaps, we pose the following main research question: How does the perceived recommender system's ability to learn influence the perceived trustworthiness of recommended product descriptions provided by the system?

We involve two additional constructs to investigate the effects of perceived ability to learn on perceived product description trustworthiness. That is, we consider consumer self-extension (Belk, 2013) into system recommendations and the perceived system anthropomorphism (Blut et al., 2018). We propose that the perceived system ability to learn may increase trustworthiness. Moreover, this relationship may be mediated by self-extension in the case of a system long-term users. Then, we investigate the role of system intelligence cues. Specifically, we propose that the positive effect of system ability-to-learn cues (like asking about preferences) is enhanced by system anthropomorphic cues (like first-person and conversation-like communication).

Below we develop our conceptual model (summarized in Fig. 1) and hypotheses. Next, we test the hypotheses in two studies (Study 1 and Study 2) among young adults participating in an online research panel. In both studies, the participants were exposed to descriptions of smartphones ostensibly recommended by a system. Noteworthy, to isolate the impact of perceived system ability to learn on the perceived trustworthiness of a particular system offering's from the actual quality of the system recommendations, we kept the same product offering presented by a system for all participants in both studies. In Study 1, we surveyed actual users of Facebook. We considered Facebook as an intelligent system recommending various content, including commercial offerings. The participants rated perceived ability to learn, self-extension, and perceived trustworthiness. Measurements were pooled into single indices and analyzed with a PROCESS mediation model. Study 2 was an experiment using a fictitious system. Ability-to-learn cues (like asking about preferences; present vs. absent) and anthropomorphic cues (like first-person and conversation-like communication; present vs. absent) were manipulated between-subject. The participants rated perceived ability to learn, perceived anthropomorphism, and trustworthiness. Measurements were pooled into single indices and analyzed with ANOVA and PROCESS moderated mediation models. In both studies, measurement scales were assessed with EFA and CFA.

This paper extends the existing knowledge on consumer response to recommender systems by linking the perceived system ability to learn and the perceived trustworthiness of recommended product descriptions (with the evaluated offerings unchanged). Moreover, we add to the literature on consumer self-extension by evidencing its mediating role in the relationship between perceived system ability to learn and recommended description trustworthiness. Eventually, we extend the literature on recommender anthropomorphism. Namely, we demonstrate how system anthropomorphic cues may enhance the degree to which system ability-to-learn cues improve the perceived ability to learn and the description trustworthiness. The results may guide marketers, managers, IT developers, and policymakers dealing with AI-based systems through the possible consequences of developing AI technology in recommender systems.

## Theoretical development

### *A recommender system's perceived ability to learn and the perceived trustworthiness of recommended product descriptions*

Rijsdijk et al. (2007) defined the ability of an intelligent product (or innovation) to learn as "product's ability to improve the match between its functioning and its environment" and to "store information and consequently adapt to its environment […] over time, which may result in better performance" (p. 342). The ability to learn is considered a key component of recommender system intelligence (Gretzel, 2011). We use this concept regarding consumers as part of the environment. Consequently, we understand the system's ability to learn about a consumer as the ability to improve the match between system functioning and the consumer by storing information related to the consumer and adapting to the consumer over time.

Previous research shows several positive consequences of product/system ability to learn. Product ability to learn is positively related to satisfaction with the product (Rijsdijk et al., 2007). The recommender system's ability to learn about a consumer may increase the perceived

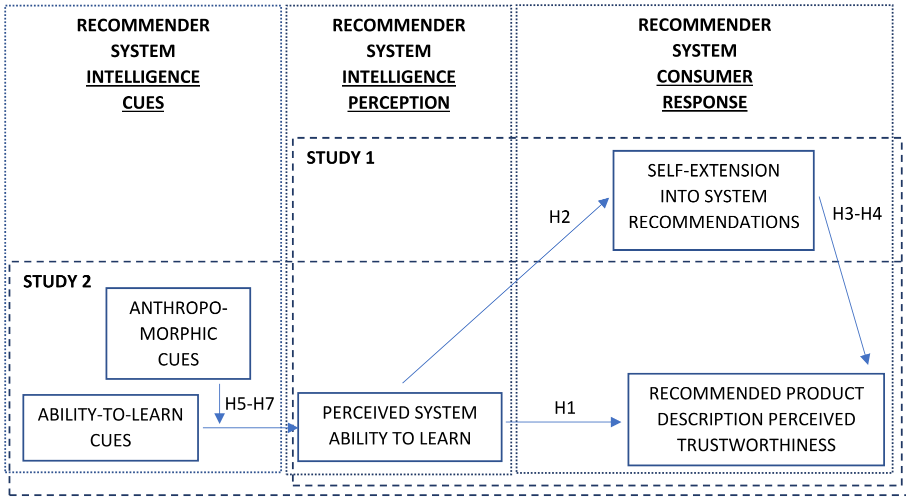


**Fig. 1.** Conceptual model.

similarity between the consumer and the system in terms of preferences and goals. This similarity may, in turn, enhance the system's use by consumers (Xiao & Benbasat, 2007). In an experiment by Kim and Duhachek (2018), when a recommender system was depicted as able to learn about consumer preferences, high (vs. low-) construal product message was more persuasive. This result suggests that perceiving a system as more able to learn allows it to provide consumers with more abstract product descriptions that consumers typically prefer to be provided by humans (vs. machines) (Kim & Duhachek, 2018, 2020).

Another possible consequence of a recommender system perceived ability to learn is the perceived trustworthiness of the information provided by a system. In the online context, product information trustworthiness, defined as the degree to which an online-accessible statement is perceived as trustworthy, reliable, and credible, is demonstrated to be positively related to product attitudes when the product information is positive (Pan & Chiou, 2011). The focal outcome considered in this paper is the perceived recommended product description trustworthiness. We define it as the degree to which a system's users believe that the descriptions that the system provides for the recommended products are trustworthy.

Although indirectly, the existing literature suggests that the recommender system perceived ability to learn about their users and the trustworthiness of system information may be related. First, a highly able-to-learn recommender system may ask consumers for or actively collect personal information on their needs, preferences, or lifestyle. In turn, the more information consumers provide about themselves, the more they may consider themselves participating in the interactions with the system. This perceived participation may lead to system trust (Dabholkar & Sheng, 2012). Likewise, Arya et al. (2019) evidenced that digital footprint (i.e., the amount of visitor-related information left when using a website) may enhance the positive impact of mobile app use on attachment to the app. Perceived interactivity, potentially resulting from the system's ability to learn, may make consumers feel they may evaluate an offering like in a physical store (Lim et al., 2020), which may also contribute to system trust. Second, the product's perceived ability to learn is demonstrated by Rijsdijk et al. (2007) to be related to that product's perceived compatibility with the consumer, which in turn may be connected with perceiving the offering as personalized. This perception may increase system trust. A notable study by Komiak and Benbasat (2006) links trust in a recommender system with the personalization of its recommendations. Those authors define personalization as the extent to which the system understands and represents a particular consumer and their needs through the recommendations. Accordingly, Li (2016) underlines the uniqueness of a consumer, defining web-based personalization as delivering individualized information based on recipients' preferences. Personalization of an actual offering proposed by a recommender system is demonstrated by Komiak and Benbasat (2006) to be positively related to consumer trust in the system's competence and affective trust in the system.

Despite the considerable research effort depicted above, the relationship between system perceived ability to learn and system information trustworthiness is far from being directly evidenced. Namely, there are three main gaps in the current understanding of this relationship.

First, the previous studies do not pertain directly to the system perceived ability to learn. For example, Dabholkar and Sheng (2012) refer to perceived participation which may be a consequence of perceived ability to learn but is not equivalent to it. Namely, the participation may result from other factors than the ability to lean, like the level of consumer activity or engagement while interacting with the system. Moreover, the perceived participation does not exhaust the possible mechanisms in which the perceived ability to learn may influence the system information trustworthiness. In other words, perceiving the system as more able to learn may increase the trustworthiness regardless of the level of perceived participation. Komiak & Benbasat's (2006) study refers to system personalization, which also does not equal the perceived ability to learn. While the concept of personalization focuses on the system output (like its recommendations), the system ability to learn pertains to the system itself. Hence, the ability to learn is a dimension of system intelligence (Rijsdijk et al., 2007), and personalization is a characteristic of system advice.

Second, the existing studies focus on the actual offering provided by recommendation systems. For example, Komiak and Benbasat (2006) manipulated the actual level of personalization by exposing their participants to two versions of a system recommendation, one of which (the high-personalization condition) referred to preferences previously declared by the participants. Li (2016) distinguished between actual and perceived personalization, providing empirical evidence that those two constructs are not equivalent. For example, Li (2016) manipulated the actual personalization by providing a message related to a participant's preferred travel destination (vs. a generic destination in a non-personalized condition). In regression models, only perceived personalization (and not actual) significantly affected ad attitude and purchase intention. Those findings suggest that perceived personalization is also shaped by factors other than actual personalization. Therefore, it remains understudied whether the positive effect on trust evidenced by Komiak and Benbasat (2006) holds for the unchanged system recommendations.

Finally, the above studies pertain to the trust in a recommender system instead of the system information perceived trustworthiness. Trust in a recommender system is a multidimensional construct comprising cognitive and emotional aspects (Komiak & Benbasat, 2006). Specifically, those authors define trust in a recommender system as a belief that the system can provide good product recommendations, objective advice, and feelings of security and comfort while making a decision based on the system's recommendation. Dabholkar and Sheng (2012) emphasize the integrity aspect of consumers' trust in recommender systems, viewing it as a consumer's belief that a system represents the consumers' benefits over those of the vendors. To summarize, trust in a recommender system is primarily conceptualized as a set of general beliefs and feelings related to the system as a whole entity that provides product advice. As such, the system trust is substantially different than system information trustworthiness. While the first pertains to an overall evaluation of a system itself, the latter focuses on a system's output, like product descriptions provided by the system. In other words, system trust is a system-focused construct, while system information trustworthiness is an output-focused construct. This way, system information trustworthiness may be viewed as a possible consequence of system trust that is more directly connected with consumer behavioral outcomes like product attitudes Pan & Chiou, 2011).

Apart from the theoretical relevance of the gaps discussed above, they are important practically as they represent the marketers' dilemmas of designing recommender systems to improve consumer response to the recommended products. On the one hand, marketers can convince consumers that the system is able to learn about them, even apart from actually personalizing a particular offering. On the other hand, making consumers trust in the product descriptions provided by the system should improve the consumer attitudes toward the offering more directly than general trust in the system. Therefore, we aim to bridge those gaps by addressing the research question: How does a recommender system's perceived ability to learn influence the trustworthiness of the descriptions of recommended products?

Based on the above considerations, we propose that the perceived ability to learn increases the system information trustworthiness. Namely, perceiving a system as more able to learn about consumers makes them perceive the system, and in turn, its recommendations, more aligned with the consumers' needs. In turn, the consumers perceive the recommended product descriptions provided by the system as more trustworthy, credible, and reliable. Formally,

**H1**. A recommender system's perceived ability to learn is positively related to the perceived trustworthiness of recommended product descriptions provided by the system.

*The role of a recommender system user's self-extension into system recommendations*

In the case of consumers repeatedly using a recommender system (like Facebook users), a system's perceived ability to learn may lead to another positive consequence, which appears to be understudied in the existing literature. Namely, the system users may extend their selves into the system recommendations. More generally, self-extension into a product is defined as the degree to which consumers regard the product as part of themselves (Belk, 1988, 2013). Through various processes like giving, buying, and learning, consumers may treat products more and more like their second skin (Belk, 1988). For the digital objects, specific mechanisms of self-extension were proposed (Belk, 2013). Namely, the self may be "dematerialized" and "re-embodied" into a digital form. Then, this digital representation may "co-construct" the self, and personal memories may be distributed into that digital object. Self-extension may produce significant consequences for consumers, e.g., increased meaning in life (Belk, 1988), and marketing, e.g., building brand communities (Belk, 2013) and developing favorable product attitudes (Kiesler & Kiesler, 2005).

Although the existing literature provides no direct evidence of the link between a recommender system's perceived ability to learn and consumer self-extension into the system recommendations, various indirect suggestions are visible. Namely, when a system can learn about a consumer, it is more consistent with the consumer's values, experiences, and needs (Rijsdijk et al., 2007). Thus, it may be treated by the consumers as part of their identities. When computer users perceived it as similar to themselves, they tended to attribute success to the computer and seek failure outside the computer, which resembles self-servicing bias (Nass & Moon, 2000) and may indicate the degree of user identification with the computer. As the highly able-to-learn system uses a large amount of self-relevant information on customers' preferences (cf. Xiao & Benbasat, 2007), the consumers may feel more tied to the system. Accordingly, the perceived similarity between a recommendation system's offerings and consumer expectations and values is proposed to increase consumer identification with the recommendation system (Lukyanenko & Komiak, 2011). Tran et al. (2020) demonstrated the positive relationship between the perceived personalization of Facebook ads and brand identification. Technology-based tools providing personalized information may make consumers consider the recommended products a new version of themselves (Del Bucchia et al., 2021). Consumers may even treat the personalized recommendation as formulated by themselves (Hamilton et al., 2020).

Consumer identification with a system offering may also be enhanced by perceived participation that may result, as discussed above, from the system's ability to learn. Namely, consumers may perceive self-made objects (here: the system recommendations) as part of their selves (Kuchmaner, 2020). Kiesler and Kiesler (2005) reported that consumers who produced a product for themselves (vs. for sale) perceived it as more symbolizing them. Accordingly, the quality of online product customization (its value congruence and distinctiveness) may increase consumer identification with the products (Kwon et al., 2017).

Despite the above notions and findings suggesting a link between a recommender system's perceived ability to learn and consumer self-extension into the system recommendations, the existing literature lacks direct evidence. This gap is important theoretically and represents the practical issue of building positive consumer attitudes towards, engagement in, and attachment to the products offerings provided by recommender systems. To bridge that gap, we pose the following research questions: How does a recommender system's perceived ability to learn influence the self-extension of its long-term users into the system recommendations? What are the consequences of that influence for the system information perceived trustworthiness?

Based on the above considerations, we propose that perceiving a recommender system as more able to learn about consumers makes the long-term system users extend themselves into the system recommendations. First, consumers may regard the system that is highly able to learn about them as more capable of presenting the product offering that is closely connected with their needs and preferences. Consequently, if those consumers are long-term system users, they may develop a firm belief that such a system actually presents the products which well represent the consumers. Therefore, such consumers may identify with the system recommendations and regard them as part of their selves. This process may go along several mechanisms that Belk (2013) proposed for self-extension in the digital context. For example, providing personal information to a highly able-to-learn system may "dematerialize" the consumer's self into this information, which may be perceived as embedded in system recommendations. In turn, those consumers may be "reembodied" in this form of digital representation. They may also be "co-constructed" by these kinds of recommendations that represent them. Thus, we aim to test the following hypothesis:

**H2**. A recommender system's perceived ability to learn is positively related to the system user's self-extension into the system recommendations.

Consumer self-extension into system recommendations may, in turn, lead to positive responses to the system and its offering, including trust.

In general, treating an object as a part of the self may lead to positive attitudes towards that object (Kiesler & Kiesler, 2005). Identification with the product is positively related to product attitude (Kwon et al., 2017). When people identify with an object, they may trust more in the related brand (Pan & Phua, 2021). Likewise, brand identification may increase brand loyalty (Kucharska et al., 2020), brand self-congruity may improve brand attachment and loyalty (Das, 2014; Kressmann et al., 2006; Liu et al., 2012; Rabbanee et al., 2020). Perceiving a recommender system as belonging to the consumer may induce positive consumer emotions (Klaus & Zaichkowsky, 2020). That kind of system, even if making errors, may be perceived as more authentic, which may lead consumers to trust and acceptance (Neururer et al., 2018). Put together, considering system recommendations as part of the self may lead to favorable attitudes toward those recommendations, and those attitudes may transfer to a higher trust in the provided information, that is, the recommended product descriptions. Therefore, we propose that consumer self-extension into system recommendations increases the perceived trustworthiness of the recommended product descriptions. Consequently, self-extension may serve as a mechanism of the positive influence of the system's perceived ability to learn on the system information trustworthiness. Formally,

**H3**. A recommender system user's self-extension into the system recommendations is positively related to the perceived trustworthiness of the recommended product descriptions provided by the system.

**H4**. The relationship between a recommender system's perceived ability to learn and the perceived trustworthiness of recommended product descriptions provided by the system (H1) is mediated by the system user's self-extension into the system recommendations.

*The role of a recommender system's intelligence cues*

Classical experiments showed that people infer human intelligence based on certain cues like physical attractiveness or speech fluency (Borkenau, 1993). Likewise, people use various cues to infer the objects' artificial intelligence. Machine Agency and Human-AI Interaction Model (Sundar, 2020) recognizes various cues related to AI-based systems as a key mechanism ("cue route") of forming user perception of those systems. Those cues are based on system-related information that consumers may acquire. Such cues do not involve system outputs resulting from interactions and collaboration with the system. For example, a recommender system may be depicted as more or less capable of learning (Araujo, 2018; Kim & Duhachek, 2018) or may show it by asking direct questions about consumer preferences (e.g., Komiak & Benbasat, 2006). A conversational software may be perceived as more autonomous when it controls the pace of the conversation with a user (Bergner et al., 2019). Such cues may be critical in the case of a recommender system that is new to a user. Without former experiences in interactions with the system, consumers are less capable of evaluating its intelligence based on its outputs (like the recommended product offerings). In other words, while long-term system users' response to the system may depend more on "action route" that is based on the results of interactions and collaboration with the system (cf. Sundar, 2020), users unfamiliar with the system may rely more on "cue route" in perceiving the system intelligence. Consequently, it is reasonable to suppose that, in the case of the system that is new to its users, ability-to-learn cues (like asking about preferences) may influence the system perceived ability to learn, and then, the system perceived information trustworthiness.

The effectiveness of the ability-to-learn cues may depend on another dimension of system intelligence: system anthropomorphism. Namely, people may perceive inanimate objects as having human-specific traits or actions to various extents (Epley et al., 2007). Likewise, anthropomorphism is defined in the AI context as the degree to which an AI-based system appears to be human-like through having human characteristics or behavior (Blut et al., 2018). In their dimensional model of product intelligence, Rijsdijk et al. (2007) consider anthropomorphic dimensions like human-like interaction (the degree to which a product communicates and interacts in a human way) and personality (the degree to which a product shows individual characteristics like emotionality). The perception of those product intelligence dimensions is positively related to the perceived ability to learn (Rijsdijk et al., 2007). Various characteristics of a system may be considered as anthropomorphic cues, including more explicit ones like human faces (Gong, 2008), voice (Moussawi & Benbunan-Fich, 2021), or emotional messages (Gelbrich et al., 2021), as well as more subtle ones like first-person statements (Adam et al., 2020; Aggarwal & McGill, 2007; Wan et al., 2017), framing messages into conversation-type boxes (Bergner et al., 2019), and humor (Moussawi & Benbunan-Fich, 2021).

Anthropomorphism may entail various forms of positive consumer response in the AI context. For example, Blut et al. (2018) argue that human-like contact may reduce consumer uncertainty about the service process and thus increase trust. Likewise, a system with a human face icon is perceived as more trustworthy (Qiu & Benbasat, 2009), more natural (cf. Rijsdijk et al., 2007), and authentic (cf. Neururer et al., 2018). Users perceive computer agents as more trustworthy when the agents have human faces (Gong, 2008), voice, and humor (Moussawi & Benbunan-Fich, 2021).

Despite the large body of existing knowledge about system anthropomorphism, its role in the effectiveness of ability-to-learn cues is scarcely investigated. To the best of our knowledge, no study jointly evaluates the effects of anthropomorphic and ability-to-learn cues on perceived ability to learn and other downstream consequences like system information perceived trustworthiness. Besides theoretical relevance, this gap corresponds to an important practical issue of designing recommender systems to improve consumer response to the system's recommended offerings. Specifically, marketers could apply intelligence cues (related to ability-to-learn and anthropomorphism) to increase consumer trust in the recommended product descriptions provided by the system. Therefore, we pose the research question: How do recommender system anthropomorphic cues influence the effectiveness of its ability-to-learn cues on the system information perceived trustworthiness?

We propose that in the presence of anthropomorphic cues, ability-to-learn cues increase the system's perceived ability to learn more. This is because product anthropomorphism is part of its perceived intelligence (Rijsdijk et al., 2007). Specifically, consumers may conceptualize product intelligence using human intelligence as a model (Duffy, 2003; Karimova & Goby, 2021). For recommender systems, learning people's preferences may be considered by consumers a human property. Therefore, ability-to-lean cues (e.g., asking a consumer about preferences) may be viewed by consumers as congruent with anthropomorphic cues (like first-person communication). In other words, anthropomorphic cues may support the ability-to-learn ones in forming the perception of a system as an intelligent entity able to learn about its users. Thus, we predict that

**H5**. In the case of system anthropomorphic cues' presence (vs. absence), the effect of system ability-to-learn cues on the system's perceived ability to learn is more positive.

It is reasonable to combine the above considerations with the relationship between a system's perceived ability to learn and the perceived trustworthiness of the recommended product descriptions. Namely, anthropomorphic cues may enhance the effect of ability-to-learn cues on trustworthiness through the perceived ability to learn. In other words, anthropomorphic cues may make ability-to-learn cues increase more the user perception of a system's ability to learn and, in turn, increase more trust in the recommended product descriptions provided by the system. Therefore, we expect that:

**H6**. In the case of system anthropomorphic cues' presence (vs. absence), the effect of system ability-to-learn cues on the perceived trustworthiness of recommended product descriptions provided by the system is more positive.

**H7**. The mediation between ability-to-learn cues and the perceived recommended product description trustworthiness through the system's perceived ability to learn is moderated at the first stage by system anthropomorphic cues. Specifically, the indirect effect of ability-to-learn cues is more positive in the presence (vs. absence) of system anthropomorphic cues.

The above hypotheses are tested in two studies (Study 1 and Study 2). The main hypothesis, predicting the relationship between perceived system ability to learn and perceived recommended product description trustworthiness (H1), is tested in both studies. Study 1 additionally tests the hypotheses related to the role of consumer self-extension into system recommendations (H2-H4). Study 2 additionally tests the hypotheses related to the role of system intelligence cues (H5-H7).

## Study 1 – a survey of Facebook users

The role of self-extension into system recommendations seems to be rather relationship-based than transaction-based. Namely, self-extension may require a firm user-system relationship. Such a relationship is developed over time, as consumers collect experiences and increase familiarity with the system (cf. Komiak & Benbasat, 2006; Xiao & Benbasat, 2007). To grasp the effects of the long-term user relationship with the system, a correlational study based on an actually existing recommendation system and its users is suitable (cf. Zanker et al., 2019). Therefore, to test the basic prediction on the relationship between the perceived ability to learn and recommended product description perceived trustworthiness (H1) together with the predictions on the role of the self-extension (H2, H3, H4), we surveyed actual users of Facebook in Study 1. We considered Facebook a recommender system offering personalized posted content that includes commercial offerings. We exposed all the participants to the same product offering ostensibly recommended by Facebook and measured perceived description trustworthiness, self-extension, and perceived system ability to learn.

### *Participants and sampling*

Two hundred four Polish Facebook users from the ARC online consumer panel (ePanel.pl) participated in the study. The sample size was larger than the minimum sample size required in power analysis for linear regression with two predictors (here, representing self-extension and ability to learn) and a medium effect size assumed for linear regression ($f^2 = 0.15$, Cohen, 2013) (G*Power, $\beta = 0.95$, $\alpha = 0.15$, $N_{min} = 107$). The recruitment criteria were the age between 20 and 30, at least high school education, using Facebook (at least one interaction in the month preceding the study), buying products online (at least on online purchase in the three months preceding the study), and using smartphones daily. The sample was gender-balanced (55.4% females, $M_{age} = 26.3$, $SD_{age} = 2.7$; see detailed demographics in Appendix A).

### *Stimuli*

We chose smartphones as a studied product category. Smartphones are widely used, well known, and potentially produce self-extension as they are an essential part of consumer lives (Campbell et al., 2020; Del Bucchia et al., 2021; Sun et al., 2020).

As stimuli, we used twelve brief descriptions of smartphone models developed by Trzebiński, Marciniak & Gaczek (in review). The descriptions varied in the level of abstractness and shopping motive they represented. Three descriptions were based on concrete attributes (i.e., "reliable in terms of electronic systems", "fast while using apps", "high-quality photos at daylight"). The next six ones used more abstract attributes ("reliable", "fast", "high-quality photos", "network signal receiver and transmitter quality", "compatibility with the newest software", and "video quality"). The remaining three descriptions referred to smartphone benefits ("web access", "use of high-demanding apps", "entertainment"). While the first benefit ("web access") was intended to correspond to more utilitarian motives (like the smartphone's usefulness in keeping one connected), the last benefit ("entertainment") should have been more oriented toward hedonic motives. This variety of description abstractness and utilitarian vs. hedonic shopping motives was supposed to support the study's external validity by reflecting various types of product descriptions that occur in real marketplaces.

The fundamental assumption of our research was to isolate the effect of a system's perceived ability to learn on the perceived trustworthiness of a particular system offering from the effect of the actual offering characteristics. Therefore, our participants responded to the same stimuli descriptions of products recommended by a system.

### *Procedure*

The participants were asked to imagine they wanted to buy a new smartphone, and Facebook recommended various smartphone models to them. They were instructed that "Based on information about you, Facebook's algorithm automatically creates brief descriptions of products it recommends to you." Next, the participants were exposed to the twelve stimuli descriptions of smartphone models, ostensibly provided by Facebook. To further improve realism, the screen presenting the stimuli descriptions resembled the Facebook page with the Facebook logo on the top.

After being exposed to the descriptions, the participants rated the perceived trustworthiness of the recommended product descriptions listed in the stimuli (as a dependent variable). Then, we measured self-extension into Facebook recommendations (as a mediator). Next, we measured perceived Facebook ability to learn (as an independent variable). We used slider scales to measure perceived description trustworthiness, ability to learn, and self-extension.

To avoid the self-generated validity issues (Feldman & Lynch, 1988; Lunardo & Rickard, 2020), we measured the system responses in an order running counter to our hypothesized causality. That is, we started the measurements with the response to a presented Facebook smartphone offering (perceive trustworthiness), went on with the self-extension into Facebook recommendations, and finished with Facebook intelligence perception (perceived ability to learn).

We checked the perceived realism of the task (78% of the participants indicated that a "very" or "somewhat" similar situation might occur in their real-life), as well as the perceived ease of imagining the situation presented in the task (79.4% of the participants chose "very easy" or "rather easy"). The questionnaire ended with a demographic section.

### *Measurements*

#### *Dependent variable*

The participants rated the perceived description trustworthiness (PDTRUST) for each of the twelve smartphone descriptions. Each description was rated with a single item ("totally untrustworthy" = 0, "totally trustworthy" = 100). The scores were aggregated across the stimuli set (cf. Chang, 2021), and the average score for the twelve descriptions served as an index of perceived description trustworthiness.

#### *Mediating variable*

The participants evaluated self-extension into the Facebook recommendations (SELF-EXT) using a measurement scale (nine items adapted from/inspired by Ferraro et al., [2011]; Kiesler & Kiesler [2005]; Schifferstein & Zwaltkruis-Pelgrim [2008]: "The content proposed to me by Facebook speaks much about me.", "To some extent, the content proposed to me by Facebook could describe me.", "To some extent, the content proposed to me by Facebook expresses who I am.", "To some extent, the content proposed to me by Facebook expresses my preferences.", "To some extent, the content proposed to me by Facebook looks as it was prepared specially for me.", "To some degree, I could consider my Facebook as part of myself.", "I can partially identify with the content proposed to me by Facebook.", "The content proposed to me by Facebook fits the way I see myself.", "The content proposed to me by Facebook could serve as a cue on who I am."; "totally disagree" = 0, "totally agree" = 100; α = 0.947). Assuming that Facebook is a recommender system providing personalized content (like posts or commercial offerings), we refer to that content to operationalize the system recommendations.

*Independent variable*

The participants rated Facebook's perceived ability to learn about them (PAL) using a measurement scale (four items adapted from/inspired by Rijsdijk et al., [2007]: "Facebook can well learn about me and my preferences.", "Facebook knows me better and better over time.", "Facebook uses interactions with me to know me better.", "Over time, Facebook adapts better and better to me and my preferences."; "totally disagree" = 0, "totally agree" = 100; α = 0.921).

*Measurement scale assessment*

To assess the two measurement scales (i.e., self-extension (SELF-EXT) and perceived ability to learn (PAL)), we subjected those measurements to Exploratory Factor Analysis (EFA) (Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) = 0.930, Bartlett's $p < .001$; extraction Method: Principal Component Analysis (PCA), VARIMAX rotation). Two components had eigenvalues above 1. The self-extension items loaded on the first component, and the ability-to-learn items loaded on the second component with loadings above the 0.5 cut-off, and loading differences between the two components above .2 (Ferguson & Cox, 1993). This result initially supports the discriminant validity of those scales. Secondly, we ran Confirmatory Factor Analysis (CFA) with the measurement scales' items. We modified the model according to modification indices and factor loadings to rich the acceptable fit. As a result, we dropped six items from the self-extension scale (SELF-EXT). The final scale consisted of three items ("The content proposed to me by Facebook speaks much about me.", "I can partially identify with the content proposed to me by Facebook.", "The content proposed to me by Facebook could serve as a cue on who I am."). The internal reliability of the reduced self-extension scale (SELF-EXT) remained satisfactory (α = 0.886). The final confirmatory model showed acceptable fit characteristics ($\chi^2(12) = 28.593$, $p = .005$, $\chi^2/df = 2.4$, RMSEA = 0.08, CFI = 0.99, TLI = 0.97, SRMR = 0.02). Composite reliabilities and AVEs were satisfactory for both scales ($CR_{PAL} = .926$, $AVE_{PAL} = .758$, $CR_{SELF\text{-}EXT} = 0.887$, $AVE_{SELF\text{-}EXT} = 0.723$), supporting convergent validity. Crucially, the correlation between the two latent variables (r = 0.784) was lower than both AVE square roots (which equaled 0.871 for ability to learn (PAL) and 0.850 for self-extension (SELF-EXT)). This result supports the discriminant validity (see details in Appendix B). Each measurement scale was pooled into a single index.

*Results*

H1 predicted the positive relationship between a recommender system's perceived ability to learn (PAL) and the perceived trustworthiness of recommended product descriptions provided by the system (PDTRUST). H2 predicted the positive relationship between the perceived ability to learn (PAL) and self-extension into the system recommendations (SELF-EXT). H3 predicted the positive relationship between self-extension (SELF-EXT) and perceived trustworthiness (PDTRUST). Eventually, H4 predicted the mediation effect of self-extension (SELF-EXT) in the relationship between the perceived ability to learn (PAL) and trustworthiness (PDTRUST) (H1). To test the above hypotheses, we ran a mediation analysis (Fig. 2, PROCESS, Model 4, 5000 bootstrap samples) with perceived ability to learn (PAL) as an independent variable, self-extension (SELF-EXT) as a mediator (VIF = 2.1), and perceived trustworthiness (PDTRUST) as a dependent variable. Ability to learn (PAL) had a positive total effect on trustworthiness (PDTRUST) (b = 0.446, t = 7.086, $p < .001$), in line with H1. The effect of perceived ability to learn (PAL) on self-extension (SELF-EXT) was also positive (b = 0.716, t = 14.592, $p < .001$), supporting H2. Self-extension (SELF-EXT) showed a positive effect on trustworthiness (PDTRUST) (b = 0.306, t = 3.477, $p = .001$), in support for H3. Finally, the indirect effect of the ability to learn (PAL) was positive (b = 0.219, 95%CI[0.084, 0.359]), supporting H4.

*Discussion*

The above results suggest that when consumers are familiar with a recommender system, as in the case with Facebook users, perceiving a system as able to learn about its users makes consumers extend their selves into a personalized content provided by the system and trust the recommended product descriptions more. Importantly, all participants responded to the same product descriptions, which ruled out the possibility of the confounding effect of the actual quality of recommended offerings. Moreover, the mediation results indicate that self-extension forms a possible mechanism of the positive effect of the perceived ability to learn on the perceived product description trustworthiness. However, the direct effect of the ability to learn is significant, which

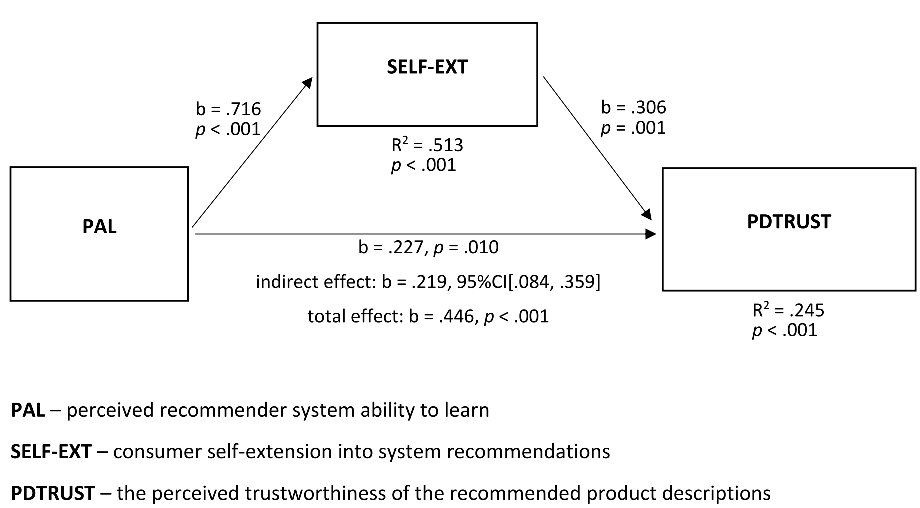


**Fig. 2.** A mediation model with perceived ability to learn as an independent variable, self-extension as a mediator, and perceived trustworthiness as a dependent variable. **PAL** – perceived recommender system ability to learn. **SELF-EXT** – consumer self-extension into system recommendations. **PDTRUST** – the perceived trustworthiness of the recommended product descriptions.

suggests that the mechanism based on self-extension is not exhaustive. Apparently, extending the self into system recommendations is not necessary to trust more in product descriptions provided by a recommender system that is perceived to be more able to learn about its users. This notion implies that the positive effect of perceived ability to learn on description trustworthiness is expectable even if a recommender system is new (unfamiliar) to consumers, and the connections built between the consumers' selves and the system are non-existent or too weak to warrant the self-extension mechanism. This conclusion provides a grounding to expect that the ability-to-learn effect on trustworthiness occurs in the presence of mere ability-to-learn cues (like asking for preferences) of a new (unfamiliar) system. That possibility is investigated experimentally in Study 2.

## Study 2 – an experiment on a fictitious recommender system

The role of system intelligence cues may be more prevalent when consumers have no or little experience with a system, and those may rely more on the immediately-accessible intelligence cues. Therefore, to check the role of system intelligence cues (H5, H6, and H7), Study 2 had a form of an experiment based on a fictitious recommender system. This experiment manipulated system intelligence cues (i.e., ability-to-learn and anthropomorphic cues). After exposing the participants to the same product offering recommended by a system, we measured perceived description trustworthiness, perceived ability to learn, and perceived anthropomorphism. We also used Study 2 to replicate testing the basic prediction on the relationship between the ability to learn and trustworthiness (H1) in the case of an unknown recommender system.

### *Participants and sampling*

Five hundred fifteen Polish consumers from the ARC online consumer panel (ePanel.pl) participated in the experiment. The study population was broader than in Study 2, as we did not require being a Facebook user. The sample size was larger than the minimum sample size required in power analysis for ANOVA with eight groups (implied by our experimental design) and a medium effect size assumed for ANOVA ($f = 0.25$, Cohen, 2013) (G*Power, $\beta = 0.95$, $\alpha = 0.05$, $N_{\min} = 400$), and the minimum sample size required in power analysis for linear regression with four predictors (here, representing our manipulations and the ability-to-learn measurement) and a medium effect size assumed for linear regression ($f^2 = 0.15$, Cohen, 2013) (G*Power, $\beta = 0.95$, $\alpha = 0.05$, $N_{\min} = 129$). The recruitment criteria were age between 20 and 30, at least high school education, buying products online (at least on online purchase in the three months preceding the study), and using smartphones daily. The sample was gender-balanced (42.1% females, $M_{age} = 26.1$, $SD_{age} = 2.8$; see detailed demographics in Appendix A).

### *Stimuli*

We used the same product category (smartphones) and the same twelve stimuli descriptions as in Study 1. Following the same goal of isolating the effect of a system's perceived ability to learn from the effect of the actual offering characteristics, the participants responded to the same stimuli descriptions in all experimental conditions.

### *Procedure*

The experimental design was a 2 (ability-to-learn cues: present vs. absent) × 2 (anthropomorphic cues: present vs. absent) × 2 (recommender type: e-commerce vs. consumer organization) between-subject. We added the recommender type factor to check whether the studied effects of system intelligence cues will differ between e-commerce recommenders and consumer organization recommenders. Consumers may perceive differently the recommendations provided by those two types of recommenders. For example, Lourenço et al. (2020) demonstrated that consumers perceive e-commerce recommenders (vs. organization recommenders) as knowing the recommended products better.

The online questionnaire consisted of three parts: an introduction with screening questions, a simulation of a fictitious recommender system (called "Electroselect") offering electronic products, and measurements. Each questionnaire part used different font types and a different background color to accentuate the above division. The participants were asked to imagine that they had decided to buy a new smartphone, and therefore they were using the recommender system.

In the present ability-to-learn cues condition, the participants were redirected to the simulation of the recommender system. Then, the system informed the participants that it aimed to learn about their needs. Next, the system asked to mark the personal values that are especially important to the participants. We used a list of thirteen values adapted from/inspired by Rokeach (1973) to fit the possible benefits of smartphones based on pretest interviews among the studied population. The list consisted of security, calmness, efficiency, exciting and interesting life, beauty, colorful memories, independence, efficacy, using opportunities, benefitting from the life, joy, and memorable moments. In the absent ability-to-learn cues condition, the same questions on personal values were asked in the screening part of the questionnaire, right before the system simulation. This way, we aimed to make the conditions different only in who is asking for the personal-values information (i.e., the recommender system vs. the researchers), with no difference in the activation of consumer self-knowledge. Our approach to manipulating the system's ability to learn may resemble that of Kim and Duhachek (2018). However, there are two major differences. First, in their study, the system asked for consumer input in both conditions, and the difference was that the system was described in the questionnaire as "fixed" or "learning." Our approach may be more realistic, as the system did not ask for consumer input in our absent ability-to-learn cues condition. Second, Kim and Duhachek (2018) asked about products bought, while we asked about personal values, which makes consumer input more self-relevant. This way, in our manipulation, the system was suggested to operate on much deeper knowledge about its user. Unlike Araujo's (2018) and Kim and Duhachek (2018) manipulations of the system's ability to learn, our cues were limited to how the system operated. We did not provide any description of a system suggesting its intelligence. This way, we intended to increase the realism of the simulation.

In the present anthropomorphic cues condition, we applied two types of cues (see Appendix C). First, the system used first-person statements (e.g., "I will present an offering."), like in Adam et al. (2020), Aggarwal and McGill (2007), and Wan et al. (2017). Additionally, system messages were framed into conversation-type boxes (Bergner et al., 2019), similar to apps used for instant messaging. In the low anthropomorphism condition, there were no first-person messages, and messages were not framed in conversation-type boxes. We used those subtle cues to avoid emotional reactions that might appear in the case of more direct cues, such as human faces (cf. Gong, 2008) or emotional messages (cf. Gelbrich et al., 2021). In pretest interviews, the participants expressed that online applications may resemble humans without an explicit human form, and the latter was associated with old-fashioned computer interfaces.

In the e-commerce recommender condition, the system was described as owned by an online shop and aimed to sell electronic products. In the consumer organization recommender condition, the system was said to be run by an independent consumer organization to help consumers make the best offering choices.

In all conditions, the participants were informed that product descriptions are created automatically by the system's algorithm. Next, all the participants were exposed to the same stimuli set of brief smartphone descriptions. Then, we measured perceived description trustworthiness (as a dependent variable), perceived recommender system ability to learn (as a mediator and manipulation check), and perceived system anthropomorphism (as a manipulation check). We used slider scales to measure perceived description trustworthiness, ability to learn, and anthropomorphism.

We measured the system responses in an order running counter to our hypothesized causality, like in Study 1. Specifically, the measurements started with consumer response to the system's offering (perceived description trustworthiness), and the system intelligence perception (ability to learn and anthropomorphism) was measured afterward.

Finally, we checked perceived realism (79.0% indicated "very" or "somewhat" similar situation might occur in real life) and perceived ease of imagining (81.0% chose "very easy" or "rather easy"). The questionnaire ended with a demographic section.

*Measurements*

*Dependent variable*

The perceived trustworthiness of the recommended product descriptions (PDTRUST) provided by the system was measured the same way as in Study 1, with the single-item measurement for each of the twelve smartphone descriptions presented in the stimuli. Like in Study 1, the average score for the twelve descriptions served as an index of perceived description trustworthiness.

*Mediating variable*

We measured perceived recommender system ability to learn (PAL) using a measurement scale (four items adapted from/inspired by Rijsdijk et al., [2007]: "Electroselect collected information from me to determine my preferences.", "Electroselect used an interaction with me to learn about my preferences.", "Electroselect collected information from me to learn something about my needs.", "I think that based on the information collected from me, Electroselect was able to adapt to me and my preferences."; “totally disagree” = 0, “totally agree” = 100; α = 0.923).

*Manipulation checks*

The measurement of perceived ability to learn (PAL) checked the ability-to-learn cues manipulation. To check the anthropomorphic cues manipulation, we measured perceived system anthropomorphism (PAN) using a measurement scale (ten items adapted from/inspired by Qiu and Benbasat [2009]; Rijsdijk et al., [2007]; Wan et al., [2017]: "Some human trait may be seen in Electroselect.", "An interaction with Electroselect looks like an interaction with a human being.", "Electroselect functions as a human being.", "While using Electroselect, I had an impression I interacted with a human being.", "While using Electroselect, I had an impression that Electroselect had a personality.", "While using Electroselect, I felt human warmth.", "While using Electroselect, I had an impression that Electroselect is sociable to some degree.", "While using Electroselect, I experienced a bit of human tenderness.", "While interacting with Electroselect, I perceived Electroselect almost like a human being.", "While interacting with Electroselect, I thought about Electroselect a bit like it was a human being."; "totally disagree" = 0, "totally agree" = 100; α = 0.974).

*Measurement scale assessment*

To assess the two measurement scales used in Study 2 (i.e., ability to learn (PAL) and anthropomorphism (PAN)), we first ran EFA (Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) = 0.953, Bartlett's $p < .001$; extraction Method: Principal Component Analysis (PCA), VARIMAX rotation). Two components had eigenvalues above 1. The anthropomorphism items loaded on the first component, and the ability-to-learn items loaded on the second component with loadings above the 0.5 cut-off, and loading differences between the two components above .2 (Ferguson & Cox, 1993). This result initially supports the discriminant validity of those scales. Secondly, the measurement scales' items were subjected to CFA. To rich the acceptable fit, we modified the model according to modification indices and factor loadings. As a result, we dropped one item with the highest modification index. That item belonged to the anthropomorphism scale (PAN) ("Some human trait may be seen in Electroselect."). The internal reliability of the reduced anthropomorphism scale remained satisfactory (α = 0.977). The final confirmatory model showed acceptable fit characteristics ($\chi^2(58) = 164.678$, $p < .001$, $\chi^2/df = 2.8$, RMSEA = 0.06, CFI = 0.99, TLI = 0.98, SRMR = 0.04). Composite reliabilities and AVEs were satisfactory for both scales ($CR_{PAL} = .924$, $AVE_{PAL} = .752$, $CR_{PAN} = .975$, $AVE_{PAN} = .814$), supporting convergent validity. Crucially, the correlation between the two latent variables (r = 0.580) was lower than both AVE square roots (which equaled 0.867 for ability to learn and 0.902 for anthropomorphism). This result supports the discriminant validity (see details in Appendix D). Each measurements scale was pooled into a single index.

*Results*

*Manipulation checks*

In the present (vs. absent) ability-to-learn cues condition, the participants showed a higher level of perceived system ability to learn (PAL) (ANOVA with ability-to-learn cues conditions, anthropomorphic cues conditions, and recommender type conditions as factors, and perceived ability to learn (PAN) as a dependent variable; $M_{present} = 60.876$, $M_{absent} = 55.273$, $F(1,507) = 7.837$, $p = .005$). No interactions with recommender type occurred.

In the present (vs. absent) anthropomorphic cues condition, the participants showed a higher level of perceived system anthropomorphism (PAN) (ANOVA with ability-to-learn cues conditions, anthropomorphic cues conditions, and recommender type conditions as factors, and perceived anthropomorphism (PAN) as a dependent variable; $M_{present} = 43.779$, $M_{absent} = 37.082$, $F(1,507) = 7.851$, $p = .005$). No interactions with recommender type occurred. The above indicates the effectiveness of both manipulations.

*Hypothesis testing*

H5 predicted that the effect of ability-to-learn cues on perceived recommender system ability to learn (PAL) is more positive in the presence (vs. absence) of anthropomorphic cues. To test this hypothesis, we ran ANOVA with ability-to-learn cues conditions, anthropomorphic cues conditions, and recommender type conditions as factors, and perceived ability to learn (PAL) as a dependent variable. There occurred an interaction effect of ability-to-learn cues conditions and anthropomorphic cues conditions on perceived ability to learn (PAL) ($F(1,507) = 9.335$, $p = .002$). Then, we ran ANOVA separately for the present and absent anthropomorphic cues conditions (Fig. 3, ability-to-learn cues conditions and recommender type conditions were factors, and perceived ability to learn (PAL) was a dependent variable). In the present anthropomorphic cues condition, the effect of ability-to-learn cues was positive ($M_{present} = 66.477$, $M_{absent} = 54.759$, $F(1,250) = 17.690$, $p < .001$). However, in the absent anthropomorphic cues condition, the effect of ability-to-learn cues was non-significant ($p > .8$). The above results support H5.

H6 predicted that the effect of ability-to-learn cues on the perceived trustworthiness of recommended product descriptions provided by the system (PDTRUST) is more positive in the presence (vs. absence) of anthropomorphic cues. To test this hypothesis, we ran ANOVA with ability-to-learn cues conditions, anthropomorphic cues conditions, and recommender type conditions as factors. The perceived description trustworthiness (PDTRUST) served as a dependent variable. There occurred the interaction effect of ability-to-learn cues conditions and anthropomorphic cues conditions on perceived description trustworthiness (PDTRUST) ($F(1,507) = 6.985$, $p = .008$). Then, we ran ANOVA separately for the present and absent anthropomorphic cues conditions (Fig. 4, ability-to-learn cues conditions and recommender type conditions were factors, and perceived description trustworthiness (PDTRUST) was a dependent variable). In the present anthropomorphic

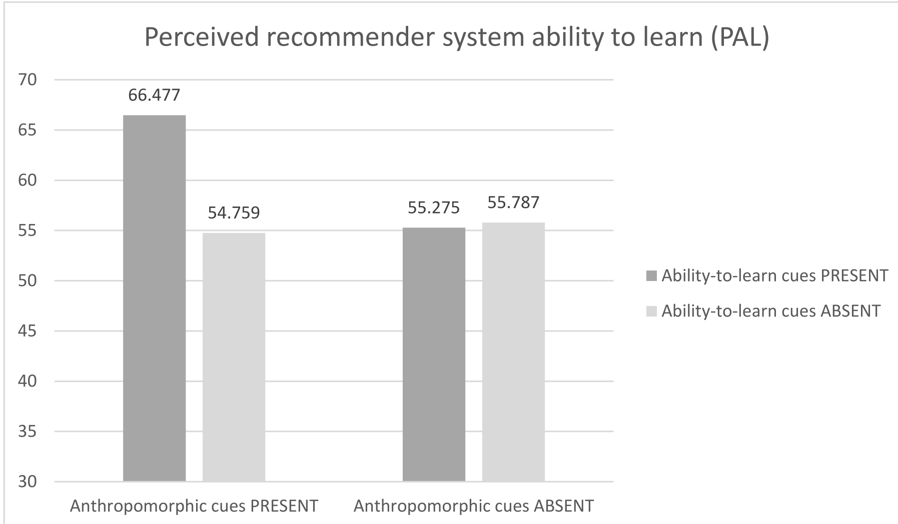


**Fig. 3.** Perceived recommender system ability to learn and system intelligence cues (Study 2).

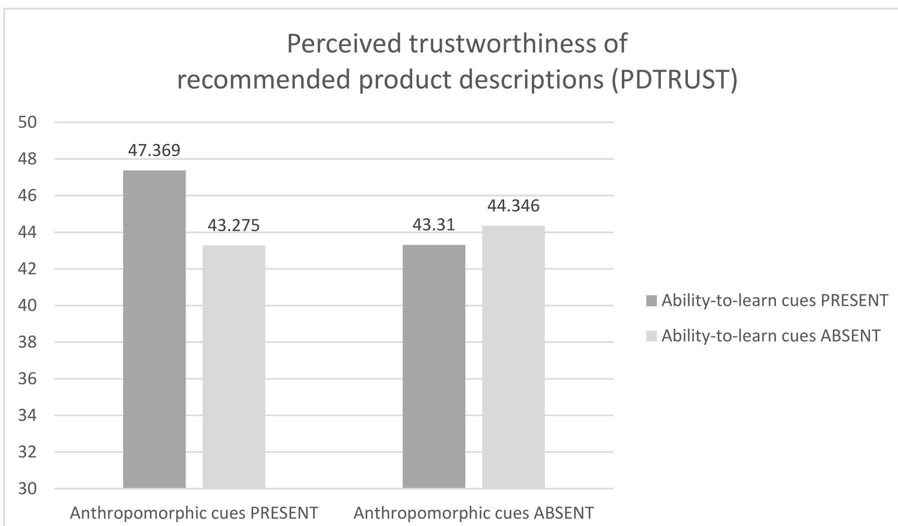


**Fig. 4.** Perceived trustworthiness of recommended product descriptions and system intelligence cues (Study 2).

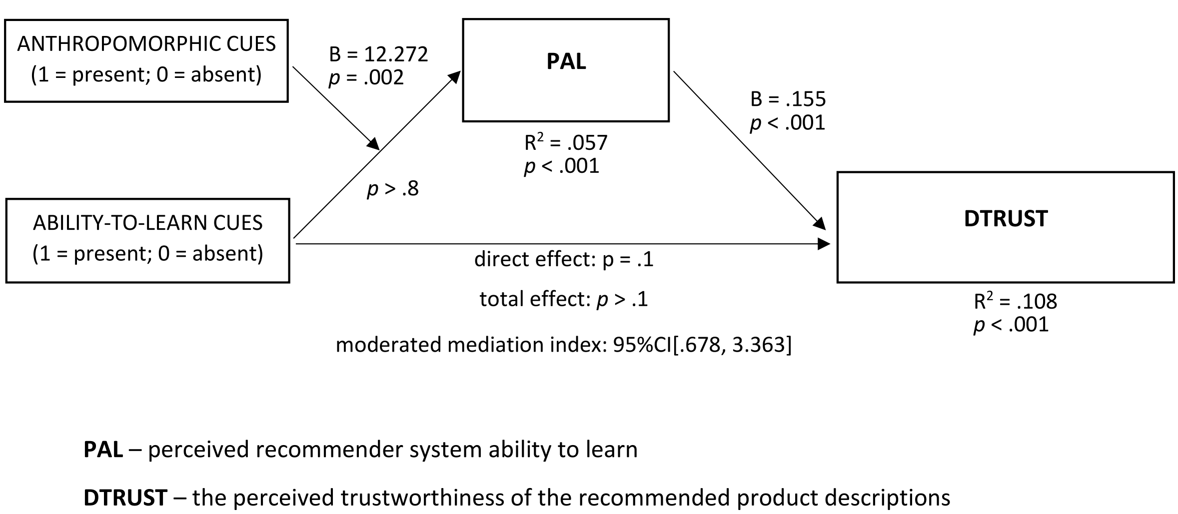


**Fig. 5.** Moderated mediation effects of system intelligence cues on the perceived trustworthiness of recommended product descriptions (Study 2). **PAL** – perceived recommender system ability to learn. **DTRUST** – the perceived trustworthiness of the recommended product descriptions.

cues condition, the effect of ability-to-learn cues was positive ($M_{present}$ = 47.369, $M_{absent}$ = 43.275, $F(1,250) = 8.580$, $p = .004$, in line with H1). However, in the absent anthropomorphic cues condition, the effect of ability-to-learn cues was non-significant ($p > .4$). The above results support H6. No interactions with recommender type occurred.

H7 was related to moderated mediation, predicting that in the case of the presence (vs. absence) of anthropomorphic cues, the indirect effect of ability-to-learn cues on the perceived trustworthiness of recommended product descriptions (PDTRUST) through perceived system ability to learn (PAL) is more positive. To test this hypothesis, we ran a first-stage moderated mediation model (Fig. 5, PROCESS Model 7, 5000 bootstrap samples) with ability-to-learn cues (dummy-coded as 1 = present, 0 = absent) as an independent variable, anthropomorphic cues (dummy-coded as 1 = present, 0 = absent) as a moderator, perceived system ability to learn (PAL) as a mediator, recommender system type as covariate (VIFs <3.1), and perceived description trustworthiness (PDTRUST) as a dependent variable. The interaction effect of ability-to-learn and anthropomorphic cues on perceived ability to learn (PAL) was positive ($B = 12.272$, $t = 3.068$, $p = .002$), and the effect of the perceived ability to learn (PAL) on the description trustworthiness (PDTRUST) was also positive ($B = 0.155$, $t = 7.699$, $p < .001$), in line with H1. Crucially, the moderated mediation index was positive ($B = 1.905$, 95%CI[0.605, 3.352]). Next, separately for each anthropomorphic-cue condition, we run the mediation model (PROCESS Model 4, 5000 bootstrap samples) with ability-to-learn cues as an independent variable, perceived system ability to learn (PAL) as a mediator, recommender system type as covariate (VIFs <1.1), and perceived description trustworthiness (PDTRUST) as a dependent variable. For the present anthropomorphic cues condition, the indirect effect of ability-to-learn cues on perceived trustworthiness (PDTRUST) through perceived ability to learn (PAL) was positive ($b = 0.157$, 95%CI[0.069, 0.264]), as well as the total effect of ability-to-learn cues on trustworthiness (PDTRUST) ($b = 0.362$, $t = 2.926$, $p = .004$), in line with H1. Moreover, the mediation was full, as the direct effect of ability-to-learn cues on trustworthiness (PDTRUST) was non-significant ($p = .1$). In support for H7, the same mediation model for the absent anthropomorphic cues condition (VIFs <1.1) produced the non-significant indirect effect of ability-to-learn cues ($p > .05$) and the non-significant total effect of ability-to-learn cues ($p > .4$). Interestingly, the effect of perceived ability to learn (PAL) on the perceived trustworthiness was significant in this model ($b = 0.314$, $t = 5.255$, $p < .001$).

### *Discussion*

First, the above results provide further experimental replication for the positive effect of ability-to-learn perception on the perceived trustworthiness of the recommended product descriptions. The ability-to-learn cues had a positive effect on trustworthiness. This finding suggests that even if a recommender system is new (unfamiliar) to consumers, like the fictitious system of Study 2, the mere ability-to-learn cues, like asking about preferences, may increase trust in product descriptions provided by the system. Importantly, the product descriptions were the same for all participants (like in Study 1), ruling out the possibility of the confounding effect of the actual offering personalization quality. However, our findings suggest an important boundary condition for this effect. Namely, the ability-to-learn cues should be accompanied by anthropomorphic cues, like first-person and conversation-like communication, to be effective. This result aligns with our expectations: we propose that anthropomorphic cues enhance the effectiveness of ability-to-learn cues in improving the perceived system's ability to learn and, in turn, the description trustworthiness. Our results support this notion based on moderation and mediation models. Lastly, the system's perceived ability to learn showed a positive effect on the description trustworthiness even when the ability-to-learn cues were ineffective in the absence of anthropomorphic cues. This finding suggests that consumers may have some general beliefs on recommender systems' ability to learn, which may be reflected and effective in the perception of a specific system, even a new one, as the fictitious system used in Study 2.

## Theoretical implications

Our research advances the existing knowledge about the effects of recommender system perceived ability to learn and personalization about a consumer on the mechanisms of consumer response to a proposed offering (e.g., Fan et al., 2020; Komiak & Benbasat, 2006; Rijsdijk et al., 2007; Tran et al., 2020) in several ways. First, while the previous related studies focused on consumer trust towards an entire recommender system (e.g., Komiak & Benbasat, 2006), our study pertains to consumer trust in the recommended product descriptions provided by the system. Specifically, we evidenced that perceiving a system as highly able to learn about consumers may lead them to trust the way the system depicts its offerings. We demonstrate this effect in two settings: (1) when perceived ability to learn results from the long-term use of a recommender system like Facebook; (2) when perceived ability to learn is induced by cues (like asking about preferences) that are embedded in a new (unfamiliar) recommender system.

Second, in contrast to the previous studies on recommender systems that predominantly relate to system personalization as a factor (e.g., Chen et al., 2020; Komiak & Benbasat, 2006; Tyrväinen et al., 2020), the system ability to learn serves as an independent variable in our study. Our results suggest that the way consumers perceive a recommender system (as more or less able to learn about them) improves their trust. Put together, the previous research efforts conclude that perceiving a recommender system offering as personalized make consumers trust more in the system. On the other hand, our research suggests that perceiving a recommender system itself as more able to learn consumers makes them trust more in the descriptions of system offerings. This notion contributes to the theory because the constructs we link (i.e., ability-to-learn perception and product description perceived trustworthiness) are much farther than the constructs linked in the previous studies. Namely, perceived personalization of a particular system's offering is rather a consequence of the system's ability to learn, and the general trust in a recommender system may be viewed as a factor of the trust in a particular set of descriptions provided by the system.

Third, compared to the previous related studies (e.g., Komiak & Benbasat, 2006), we isolated the effect of system perception (like perceived system ability to learn) on consumer response (like the perceived trustworthiness of a particular system offering) from the effect of actual offering personalization. Specifically, we evidenced the effects of the perceived ability to learn while keeping the actual offering constant. This way, we ruled out the possibility that the actual offering itself influenced the consumer response.

Fourth, we evidenced the mediating role of consumer self-extension into the system recommendations in the relationship between perceived system ability to learn and the perceived product description trustworthiness in the case of long-term use of a recommender system like Facebook. To the best of our knowledge, this study is the first one to link perceived system ability to learn, self-extension, and product description trustworthiness.

Fifth, our research demonstrates that the effect of ability-to-learn cues (like asking about preferences) on perceived ability to learn and consumer trust may be enhanced by anthropomorphic cues (like first-person and conversational-like communication). This way, we offer a possible boundary condition for the effectiveness of ability-to-learn cues.

Sixth, our research adds to the literature on self-extension in digital contexts (e.g., Belk, 2013). Specifically, our results suggest that the self-extension into the system recommendations may be increased by perceiving the system as able to learn about its users, contributing to building trust in the system offering descriptions.

Finally, we extend the existing knowledge on intelligent product/

system anthropomorphism (Blut et al., 2018; Gong, 2008; Moussawi & Benbunan-Fich, 2021; Qiu & Benbasat, 2009; Rijsdijk et al., 2007). Namely, we evidence that anthropomorphic cues enhance the effectiveness of ability-to-learn cues in improving the perception of system ability to learn and consumer trust. This way, we support the notion of Rijsdijk et al. (2007), who consider anthropomorphic dimensions as an integral part of product perceived intelligence.

## Practical implications

Our research guides marketers, managers, and IT developers who use recommender systems to present product offerings. Namely, our results suggest those professionals can build consumer trust in the recommended offerings by inducing the mere perception of a system as able to learn about a consumer *without* personalizing the actual offerings. Specifically, the system can ask its users to characterize their lifestyles. Those positive effects can be fostered by making a system more anthropomorphic, even based on subtle cues like first-person messages and conversation-type message boxes. Moreover, investing in the perception of a recommender system as highly able to learn about its users may enable building strong connections between consumers and the recommendations provided by the system. Importantly, marketers may expect that this form of identification should further enhance consumer trust in the product descriptions provided by the system.

For consumers and policymakers, our research sends a warning signal. Namely, consumers appear prone to system intelligence cues (even simple ones), responding more positively to an offering description even if it is actually *not* personalized. Therefore, consumers exposed to an intelligent system recommendation should be encouraged to ask themselves: Is the offering is actually compatible with me? Would I react so positively to the offer if the system contained no sign of intelligence?

## Limitations and directions for further research

The mechanisms of the consumer response to an offering proposed by a recommender system may depend on a product category and consumer characteristics. For example, we chose smartphones as we consider them as high-involving, widely used, and potentially easy to induce self-extension. One may thus ask if the same effects hold for low-involvement products. Smartphones are technologically advanced products, so a higher interest in technology may simultaneously impact the perception of a system and a smartphone offering. Our participants were educated and aged 20–30, which makes them probably tech-savvier than, for example, older or less educated consumers. Therefore, it is worth considering various product categories and consumer groups to investigate further the mechanisms studied in this paper. Likewise, we may expect long-term changes in those mechanisms as people become more familiar with intelligent technologies. For example, in qualitative pretest interviews conducted for our study, the participants told us that a few years ago, they were encountering many apps using a human avatar to make an app more human-like, but nowadays it would be rather "weird," and it is easy for people to get in touch with an app without a human avatar. Similarly, consumers may change their perceptions of the system's ability to learn. Therefore, future research may check the extent to which the studied mechanisms will still be valid.

In our experiment (Study 2), we used subtle anthropomorphic cues. Precisely, the recommender system did not resemble a human being to the extent that it would induce the uncanny valley effect (Akdim et al., 2021; Følstad et al., 2018; Mende et al., 2019). Consequently, we demonstrated that those subtle anthropomorphic cues might enhance the positive impact of the ability to learn on consumer trust. However, it would be interesting to study a possibly inverted U-shaped relationship when adding an extreme-anthropomorphism condition.

We have not exhausted the possible downstream consequences of system intelligence. For example, it is worth investigating the impact of perceived system ability to learn and system intelligence cues on purchase intention and consumer actual product choice using field experiments. Also, one may study consumer traits moderating the system intelligence effects. For example, narcissism may lead to higher persuasiveness of personalized advertising (Bang et al., 2019). Thus, that trait may enhance the role of the perceived system ability to learn in positive consumer responses to an offering recommended by the system.

## Funding

National Science Centre Poland (NCN), grant no. 2018/02/X/HS4/03328

## Declaration of competing interest

I declare no conflict of interest regarding our submission of the manuscript

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2022.100193.

## References

Abumalloh, R., Ibrahim, O., & Nilashi, M. (2020). *Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce*. Technology in Society, Article 101253.

Adam, M., Wessel, M., & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 1–19.

Aggarwal, P., & McGill, A. L. (2007). Is that car smiling at me? Schema congruity as a basis for evaluating anthropomorphized products. *Journal of Consumer Research, 34*(4), 468–479.

Akdim, K., Belanche, D., & Flavián, M. (2021). Attitudes toward service robots: Analyses of explicit and implicit attitudes based on anthropomorphism and construal level theory. *International Journal of Contemporary Hospitality Management* (ahead-of-print).

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85*, 183–189.

Araujo, T., Copulsky, J. R., Hayes, J. L., Kim, S. J., & Srivastava, J. (2020). From purchasing exposure to fostering engagement: Brand–consumer experiences in the emerging computational advertising landscape. *Journal of Advertising, 49*(4), 428–445.

Ariely, D. (2000). Controlling the information flow: Effects on consumers' decision making and preferences. *Journal of Consumer Research, 27*(2), 233–248.

Arya, V., Sethi, D., & Paul, J. (2019). Does digital footprint act as a digital asset?– Enhancing brand experience through remarketing. *International Journal of Information Management, 49*, 142–156.

Bang, H., Choi, D., Wojdynski, B. W., & Lee, Y. I. (2019). How the level of personalization affects the effectiveness of personalized ad messages: The moderating role of narcissism. *International Journal of Advertising, 38*(8), 1116–1138.

Belk, R. W. (1988). Possessions and the extended self. *Journal of Consumer Research, 15*(2), 139–168.

Belk, R. W. (2013). Extended self in a digital world. *Journal of Consumer Research, 40*(3), 477–500.

Bergner, A., Hildebrand, C., & Häubl, G. (2019). Conversational interfaces as persuasion instruments: Implications for consumer choice and brand perceptions. *ACR North American Advances, 47*, 259–264.

Blut, M., Wünderlich, N., & Brock, C. (2018). *Innovative technologies in branded-service encounters: How Robot characteristics affect brand trust and experience, social Robots in the branded service encounter*. Thirty Ninth International Conference on Information Systems.

Borkenau, P. (1993). *How accurate are judgments of intelligence by strangers?* Annual Meeting of the American Psychological Association – Reports.

Campbell, S. W., Wang, E. W., & Bayer, J. B. (2020). Mobiles and the self: A trajectory of paradigmatic change. In R. Ling, L. Fortunati, G. Goggin, S. S. Lim, & Y. Li (Eds.), *The Oxford Handbook of Mobile Communication and Society*. Oxford University Press.

Chang, C. (2021). How morality judgments influence humor perceptions of prankvertising. *International Journal of Advertising, 40*(2), 246–271.

Chen, T., Guo, W., Gao, X., & Liang, Z. (2020). *AI-based self-service technology in public service delivery: User experience and influencing factors*. Government Information Quarterly, Article 101520.

Chouk, I., & Mani, Z. (2019). Factors for and against resistance to smart services: Role of consumer lifestyle and ecosystem related variables. *Journal of Services Marketing, 33*(4), 449–462.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Routledge.

Dabholkar, P. A., & Sheng, X. (2012). Consumer participation in using online recommendation agents: Effects on satisfaction, trust, and purchase intentions. *Service Industries Journal, 32*(9), 1433–1449.

Das, G. (2014). Impacts of retail brand personality and self-congruity on store loyalty: The moderating role of gender. *Journal of Retailing and Consumer Services, 21*(2), 130–138.
Del Bucchia, C., Miltgen, C. L., Russell, C. A., & Burlat, C. (2021). Empowerment as latent vulnerability in techno-mediated consumption journeys. *Journal of Business Research, 124*, 629–651.
Desai, D. (2019). An empirical study of website personalization effect on users intention to revisit E-commerce website through cognitive and hedonic experience. In *Data Management, Analytics and Innovation*. Singapore: Springer.
Duffy, B. R. (2003). Anthropomorphism and the social robot. *Robotics and Autonomous Systems, 42*(3–4), 177–190.
Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864–886.
Fan, X., Ning, N., & Deng, N. (2020). The impact of the quality of intelligent experience on smart retail engagement. *Marketing Intelligence & Planning, 38*(7), 877–891.
Feldman, J. M., & Lynch, J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of Applied Psychology, 73*(3), 421–435.
Ferguson, E., & Cox, T. (1993). Exploratory factor analysis: A users' guide. *International Journal of Selection and AsSessment, 1*(2), 84–94.
Ferraro, R., Escalas, J. E., & Bettman, J. R. (2011). Our possessions, our selves: Domains of self-worth and the possession–self link. *Journal of Consumer Psychology, 21*(2), 169–177.
Følstad, A., Nordheim, C. B., & Bjørkli, C. A. (2018, October). What makes users trust a chatbot for customer service? An exploratory interview study. In *International Conference on Internet Science*. Cham: Springer.
Gaber, H. R., Wright, L. T., & Kooli, K. (2019). Consumer attitudes towards Instagram advertisements in Egypt: The role of the perceived advertising value and personalization. *Cogent Business & Management, 6*(1), Article 1618431.
Gao, B., & Huang, L. (2019). Understanding interactive user behavior in smart media content service: An integration of tam and smart service belief factors. *Heliyon, 5*(12), Article e02983.
Gelbrich, K., Hagel, J., & Orsingher, C. (2021). Emotional support from a digital assistant in technology-mediated services: Effects on customer satisfaction and behavioral persistence. *International Journal of Research in Marketing, 38*(1), 176–193.
Gong, L. (2008). How social is social responses to computers? The function of the degree of anthropomorphism in computer representations. *Computers in Human Behavior, 24*(4), 1494–1509.
Gretzel, U. (2011). Intelligent systems in tourism: A social science perspective. *Annals of Tourism Research, 38*(3), 757–779.
Hamilton, K. A., Lee, S. Y., Chung, U. C., Liu, W., & Duff, B. R. (2020). Putting the "Me. In *endorsement: Understanding and conceptualizing dimensions of self-endorsement using intelligent personal assistants*. New Media & Society, 1461444820912197.
Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science, 19*(1), 4–21.
Karimova, G. Z., & Goby, V. P. (2021). The adaptation of anthropomorphism and archetypes for marketing artificial intelligence. *Journal of Consumer Marketing, 38*(2), 229–238.
Kiesler, T., & Kiesler, S. (2005). My pet rock and me: An experimental exploration of the self extension concept. *ACR North American Advances, 32*, 365–370.
Kim, T. W., & Duhachek, A. (2018). The impact of artificial agents on persuasion: A construal level account. *ACR Asia-Pacific Advances, 12*, 53-53.
Kim, T. W., & Duhachek, A. (2020). Artificial intelligence and persuasion: A construal-level account. *Psychological Science, 31*(4), 363–380.
Klaus, P., & Zaichkowsky, J. (2020). AI voice bots: A services marketing research agenda. *Journal of Services Marketing, 34*(3), 398-398.
Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 941–960.
Kressmann, F., Sirgy, M. J., Herrmann, A., Huber, F., Huber, S., & Lee, D. J. (2006). Direct and indirect effects of self-image congruence on brand loyalty. *Journal of Business Research, 59*(9), 955–964.
Kucharska, W., Confente, I., & Brunetti, F. (2020). The power of personal brand authenticity and identification: Top celebrity players' contribution to loyalty toward football. *The Journal of Product and Brand Management, 29*(6), 815–883.
Kuchmaner, C. A. (2020). *Are you for real? The consumption-driven self-authentication process and its effects on perceived brand authenticity, Doctoral dissertation*. Kent State University.
Kwon, S., Ha, S., & Kowal, C. (2017). How online self-customization creates identification: Antecedents and consequences of consumer-customized product identification and the role of product involvement. *Computers in Human Behavior, 75*, 1–13.
Labecki, A., Klaus, P., & Zaichkowsky, J. L. (2018). How bots have taken over brand choice decisions. In *Proceedings of the Future Technologies Conference*. Cham: Springer.
Li, C. (2016). When does web-based personalization really work? The distinction between actual personalization and perceived personalization. *Computers in Human Behavior, 54*, 25–33.
Lim, J., Wollscheid, J. R., & Ayyagari, R. (2020). Examining the effectiveness of compensatory adaptation from a consumer's perspective in evaluating products online. *American Journal of Business, 35*(2), 61–81.
Liu, F., Li, J., Mizerski, D., & Soh, H. (2012). Self-congruity, brand attitude, and brand loyalty: A study on luxury brands. *European Journal of Marketing, 46*(7/8), 922–937.
Lourenço, C. J., Dellaert, B. G., & Donkers, B. (2020). Whose algorithm says so: The relationships between type of firm, perceptions of trust and expertise, and the acceptance of financial Robo-advice. *Journal of Interactive Marketing, 49*, 107–124.
Lukyanenko, R., & Komiak, S. (2011). *Designing recommendation agents as extensions of individual users: Similarity and identification in web personalization*. Thirty Second International Conference on Information Systems.
Lunardo, R., & Rickard, B. (2020). How do consumers respond to fun wine labels? *British Food Journal, 122*(8), 2603–2619.
Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535–556.
Moussawi, S., & Benbunan-Fich, R. (2021). The effect of voice and humour on users' perceptions of personal intelligent agents. *Behaviour & Information Technology, 40*(15), 1603–1626.
Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues, 56*(1), 81–103.
Neururer, M., Schlögl, S., Brinkschulte, L., & Groth, A. (2018). Perceptions on authenticity in chat bots. *Multimodal Technologies and Interaction, 2*(3), 60.
Nguyen, Q. N., & Sidorova, A. (2018). *Understanding user interactions with a chatbot: A self-determination theory approach*. Americas Conference on Information Systems.
Pan, L. Y., & Chiou, J. S. (2011). How much can you trust online information? Cues for perceived trustworthiness of consumer-generated online information. *Journal of Interactive Marketing, 25*(2), 67–74.
Pan, P. L., & Phua, J. (2021). Connecting sponsor brands through sports competitions: An identity approach to brand trust and brand loyalty. *Sport, Business and Management: International Journal, 11*(2), 164–184.
Prentice, C., Weaven, S., & Wong, I. A. (2020). Linking AI quality performance and customer engagement: The moderating effect of AI preference. *International Journal of Hospitality Management, 90*, Article 102629.
Qiu, L., & Benbasat, I. (2009). Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems, 25*(4), 145–182.
Rabbanee, F. K., Roy, R., & Spence, M. T. (2020). Factors affecting consumer engagement on online social networks: Self-congruity, brand attachment, and self-extension tendency. *European Journal of Marketing, 54*(6), 1407–1431.
Rhee, C. E., & Choi, J. (2020). Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. *Computers in Human Behavior*, Article 106359.
Rijsdijk, S. A., Hultink, E. J., & Diamantopoulos, A. (2007). Product intelligence: Its conceptualization, measurement and impact on consumer satisfaction. *Journal of the Academy of Marketing Science, 35*(3), 340–356.
Rokeach, M. (1973). *The nature of human values*. Free Press.
Schifferstein, H. N., & Zwartkruis-Pelgrim, E. P. (2008). Consumer-product attachment: Measurement and design implications. *International Journal of Design, 2*(3), 1–13.
Sivaramakrishnan, S., Wan, F., & Tang, Z. (2007). Giving an "e-human touch" to e-tailing: The moderating roles of static information quantity and consumption motive in the effectiveness of an anthropomorphic information agent. *Journal of Interactive Marketing, 21*(1), 60–75.
Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human–AI interaction (HAII). *Journal of Computer-Mediated Communication, 25*(1), 74–88.
Sun, Y., Yang, C., Shen, X. L., & Wang, N. (2020). When digitalized customers meet digitalized services: A digitalized social cognitive perspective of omnichannel service usage. *International Journal of Information Management, 54*, Article 102200.
Swaminathan, V. (2003). The impact of recommendation agents on consumer evaluation and choice: The moderating role of category risk, product complexity, and consumer knowledge. *Journal of Consumer Psychology, 13*(1–2), 93–101.
Tran, T. P., Lin, C. W., Baalbaki, S., & Guzmán, F. (2020). How personalized advertising affects equity of brands advertised on Facebook? A mediation mechanism. *Journal of Business Research, 120*, 1–15.
Trzebiński, W., Marciniak, B., & Gaczek, P. (in review), Is it better to communicate product information abstractly or concretely? The role of consumer product expertise and shopping-stage mindset.
Tyrväinen, O., Karjaluoto, H., & Saarijärvi, H. (2020). Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. *Journal of Retailing and Consumer Services, 57*, Article 102233.
Wan, E. W., Peng Chen, R., & Jin, L. (2017). Judging a book by its cover? The effect of anthropomorphism on product attribute processing and consumer preference. *Journal of Consumer Research, 43*(6), 1008–1030.
Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management, 29*(5), 907–931.
Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*(1), 137–209.
Yoon, V. Y., Hostler, R. E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. *Decision Support Systems, 55*(4), 883–893.
Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. *International Journal of Human-Computer Studies, 131*, 160–168.
Zhang, W., Leng, X., & Liu, S. (2020). Research on mobile impulse purchase intention in the perspective of system users during COVID-19. *Personal and Ubiquitous Computing*, 1–9.