Influence of human versus AI recommenders:

The roles of product type and cognitive processes

Abstract

Previous research suggests that consumers would listen more to product recommendations from other consumers (human recommenders) than from systems based on artificial intelligence (AI recommenders). We hypothesize that this might depend on the type of product being recommended, and propose an underlying process driving this effect. Three experiments show that, for hedonic products (but not for utilitarian products), human recommenders are more effective than AI recommenders in influencing consumer reactions toward the recommended product. This effect occurs because, when compared to AI recommenders, human recommenders elicit stronger mentalizing responses in consumers. This, in turn, helps consumers self-reference the product to their own needs. However, humanizing AI recommenders increases mentalizing and self-referencing responses, thus increasing the effectiveness of this type of recommenders for hedonic products. Together, these findings provide insight into *when* and *why* consumers might rely more on product recommendations from humans as compared to AI recommenders.

Keywords: product recommendations; artificial intelligence; hedonic product; utilitarian product; mentalizing; self-referencing

1. Introduction

Consumers have long relied on recommendations from other people to inform their purchasing decisions. Recommendations usually come in the form of explicit advice in which consumers suggest for other consumers which products to buy (Peluso et al., 2017). In addition, such recommendations often provide a rich description of what it is like to own or use a product (Simonson and Rosen, 2014), helping receivers relate the product to their own needs. Yet, today, consumers may also receive product recommendations from an increasing number of recommendation systems based on artificial intelligence (AI) (Araujo, 2018; Castelo et al., 2019a). Such AI recommenders use intelligent algorithms to provide consumers with relevant recommendations based on consumers' revealed interests and past online purchasing behaviors. Indeed, with rapid progress in the field of AI, suggestions provided by these recommenders might even be more accurate in reflecting consumers' individual preferences than those provided by humans (Yeomans et al., 2019). Despite the potential accuracy of AI-based recommendations, empirical evidence suggests that consumers are somewhat averse to following such recommendations (Longoni et al., 2019; Önkal et al., 2009). This phenomenon, known as "algorithm aversion" (Dietvorst et al., 2015), suggests that consumers would rather listen to advice from another human being than from an AI system using algorithmic rules. Thus, there is a general belief that, when compared to AI recommenders, humans are more effective at providing recommendations that influence consumer purchases.

In the present research, we question this general belief regarding the relative effectiveness of human recommenders (i.e., consumers providing online product recommendations; Longoni and Cian, 2020) and AI recommenders (i.e., autonomous systems providing such recommendations; Castelo et al., 2019a). Specifically, we investigate whether there are circumstances that reduce consumers' aversion against AI recommenders, and thus make such recommenders as effective in recommending products as human recommenders.

More importantly, we examine the mechanisms that could explain such effects. Building on recent works suggesting that the effects of human versus AI recommenders are context-dependent (Castelo et al. 2019a; Longoni and Cian, 2020), we aim to extend a recent research by Longoni and Cian (2020), which shows that human recommenders could be more effective than AI recommenders for hedonic versus utilitarian products. Longoni and Cian (2020) explained such differential effects of human versus AI recommenders through consumers' lay beliefs that, compared to AI recommenders, human recommenders are more competent in the hedonic consumption realm and less competent in the utilitarian consumption realm. Yet, as the two authors acknowledged in their work, beliefs about the competence of such systems might soon change as consumers will get used to obtaining AI-based recommendations also in relatively more hedonic settings, such as restaurants and movies (Yaniv et al., 2011). Hence, further and deeper insights on the fundamental mechanism underlying the aforementioned effects are needed to better understand *why* consumers may have different reactions to recommendations provided by humans versus AI-based systems.

To fill this gap, in this paper we address the following research questions:

RQ 1: Would the effectiveness of human versus AI recommenders differ depending on whether the product recommended is hedonic or utilitarian? And, if so:

RQ 2: What is the psychological mechanism that could explain the differential effectiveness of these two types of recommenders for hedonic versus utilitarian products?

To answer these questions, we empirically test the differential effectiveness of human versus AI recommenders in suggesting hedonic versus utilitarian products, and explore the underlying mechanism by investigating the sequential mediating roles of two psychological processes: *mentalizing* (i.e., one's ability to understand the mental states of others; Frith and Frith, 2006; Van Overwalle and Baetens, 2009) and *self-referencing* (i.e., one's ability to associate self-relevant incoming information with personal needs; Debevec and Romeo, 1992). We show that human recommenders are more effective in generating favorable consumer reactions (i.e., product attitude, purchase intention) than AI recommenders in the hedonic domain but not in the utilitarian domain. Furthermore, we show that this effect occurs due to human recommenders' ability to elicit stronger mentalizing responses in consumers, who thus are better able to "read" into the recommenders' minds to understand how they think and feel. This process, in turn, increases self-referencing, whereby consumers are better able to understand how the recommended product relates to their personal needs, and thereby enhances consumers' favorable reactions to the product. Importantly, this effect hinges on the perception of AI recommenders as mindless nonhuman entities, which inhibits consumers' mentalizing responses. Hence, we show that humanizing AI recommenders may be a viable tactic to enhance their ability to elicit mentalizing and self-referencing responses in consumers and, through this mechanism, to enhance the effectiveness of such recommenders in the hedonic context.

Our findings make three main contributions. Firstly, prior work on human versus AI recommenders has predominantly found the former to be more effective (e.g., Dietvorst et al., 2015; Longoni et al., 2019; Yeomans et al., 2019), and newer studies have begun focusing on contexts that might level out their difference in effectiveness (Castelo et al., 2019a; Longoni and Cian, 2020). However, there is still little knowledge concerning *why* human recommenders are more effective than AI recommenders in some circumstances but not in others. Our research advances this stream of literature by elucidating a psychological process that could give a robust understanding of *why* and *when* human-generated recommendations are more influential than AI-generated recommendations. Secondly, our findings extend the literature on mentalizing. While prior studies identify mentalizing as pivotal in distinguishing humans from robots (Gray and Wegner, 2012; Wiese et al., 2017), our research is the first to show the usefulness of this concept to compare human recommenders to AI recommenders in a consumer context. Given the ongoing debate on the effects of humans versus robots in diverse consumer settings (Castelo et al., 2019b; Mende et al., 2019), our findings are relevant to consumer theories beyond the context of product recommendations. Thirdly, our findings contribute to the literature on anthropomorphism. While prior research suggests that providing AI recommenders with human features could enhance mind perceptions (Epley et al., 2013; Gray and Wegner, 2012), there is a debate among scholars on whether this tactic has positive or negative influence on consumer reactions (Fernandes and Oliveira, 2021; Kim et al., 2019b). We add to this debate by showing a context in which humanizing AI recommenders has a positive effect on consumer reactions. Our findings suggest that this tactic might be useful at a managerial level to overcome consumers' resistance to AI-based recommendations for hedonic products.

In the following sections, we review the relevant literature on AI recommenders, as compared to human recommenders, and develop our research hypotheses. Then, we present three experimental studies, which provide empirical support to our predictions. Next, we conclude the paper by discussing the theoretical and managerial implications of our findings.

2. Theoretical background

2.1 AI versus human recommenders

An *AI recommender* refers to any type of autonomous system that uses algorithms to produce recommendations for consumers. Algorithms help AI recommenders provide personalized product recommendations, for instance, in the form of a list that sorts product alternatives by their predicted attractiveness to an individual consumer (Häubl and Murray, 2003). AI recommenders could be embodied with a (virtual) body or face (e.g., an avatar) (Holzwarth et al., 2006), or disembodied. Furthermore, they could be more human-like, for instance, by adopting a human appearance or imitating human behaviors, or be more robot-like (Araujo, 2018; Mende et al., 2019). This latter distinction is particularly relevant to this research as we compare AI recommenders with human recommenders. Indeed, anthropomorphism theory suggests that making AI agents more human-like could cause the unconscious assumption that the agents' behaviors are analogous to human behaviors, thus inducing more positive responses (Blut et al., 2021). This theory also seems to underlie companies' tendency of making their AI applications more human-like, such as humanized chatbots and virtual assistants (e.g., Amazon's Alexa). Thus, in this research we examine the effectiveness of both robot-like and human-like AI recommenders, relative to human recommenders, in influencing consumers' reactions in terms of product attitude and purchase intention.

On the other hand, a *human recommender* would either be another consumer (e.g., relatives, friends, strangers) or an expert (e.g., salespersons, independent experts) (Senecal and Nantel, 2004). In this research we focus on the former type and conceptualize human recommenders as consumers offering recommendations online. Since these recommenders are regular consumers with no vested interest in promoting a product or brand, they are sources that receivers tend to trust and rely on (Boerman et al., 2017). Human recommenders are also perceived as highly relevant and accurate sources of product information, providing others with almost perfect indication of product quality (Simonson and Rosen, 2014).

While AI recommenders have a stronger link to commercial actors than human recommenders, being designed and controlled by companies, consumers do not typically perceive AI recommenders as commercial actors with persuasive intents (Kim and Duhachek, 2020), as they would do for other types of company-controlled information sources (e.g., advertising). Consumers rather see AI recommenders as a tool helping them make relevant decisions (Senecal and Nantel, 2004). Furthermore, consumers seem also more willing to share private information to an AI recommender than to a human representative of a company (Kim et al., 2019a), indicating a higher level of trust in AI-based recommendations than in company-controlled information. Finally, given the common practice of basing algorithmic recommendations on what “similar customers to you have purchased” (Yeomans et al., 2019), it seems feasible that AI recommenders and human recommenders are considered two sources of information that in many ways promise the same to consumers: the provision of relevant and trustworthy purchase advice.

Previous research comparing these two information sources shows that AI recommenders might provide recommendations that more accurately reflect individual receivers’ needs (see Table 1 for a summary of previous research findings). Yet, a vast body of empirical evidence shows that consumers rely more on humans than AI systems related to the provision of recommendations and predictions regarding, for example, student performance (Dietvorst et al., 2015), healthcare (Longoni et al., 2019), stock prices (Önkal et al., 2009), and employee selection (Diab et al., 2011). This dominant finding in the literature has led to the notion of “algorithm aversion” (Dietvorst et al., 2015), suggesting that consumers are in general more willing to listen to human-based over AI-based recommendations.

[Insert Table 1 about here]

However, an alternative theoretical lens suggests that the reliance on either type of recommender might vary depending on the context. For instance, researchers have found that consumers will express more comfort relying on AI-based advice when the tasks seem objective (vs. subjective) (Castelo et al., 2019a) or cognition-oriented (vs. emotion-oriented) (Waytz and Norton, 2014). Also, when receiving advice for utilitarian (vs. hedonic) products, people are more influenced by AI recommenders than human recommenders (Longoni and Cian, 2020). However, the explanations for why consumers’ aversion against AI recommenders are present in some contexts and not in others might largely draw on certain transitional beliefs about AI systems that may soon be outdated. For instance, the general belief that AI recommenders are less competent in recommending hedonic products (Longoni and Cian, 2020) and less effective in performing subjective tasks (Castelo et al., 2019a) might change as people get used to AI recommenders in these contexts.

Our investigation contributes to this stream of literature by examining an explanation for the differential effectiveness of different recommender types that is rooted in fundamental psychological mechanisms. We specifically examine the sequential mediating roles of two psychological factors—namely, *mentalizing* and *self-referencing*—that could elucidate why AI and human recommenders might differ in their effectiveness at persuading consumers depending on whether the product being recommended is hedonic or utilitarian (Longoni and Cian, 2020). As such, this research proposes the moderated serial mediation model presented in Fig. 1.

[Insert Figure 1 about here]

2.2 The moderating role of product type

Products are often categorized as primarily hedonic or utilitarian (Hirschman and Holbrook, 1982). Hedonic products offer multisensory, experiential, and joyful benefits (e.g., video games, perfume), whereas utilitarian products offer practical and instrumental benefits (e.g., batteries, microwaves) (Dhar and Wertenbroch, 2000). Consumers typically purchase hedonic products to obtain pleasure-related outcomes and utilitarian products to accomplish functional or practical tasks (Chitturi et al., 2008). Importantly, the distinction between hedonic and utilitarian products is not absolute, as hedonic products may possess utilitarian benefits and utilitarian products may possess hedonic benefits (Okada, 2005). Therefore, the perception of hedonic and utilitarian products tends to be malleable and sensitive to how a product's attributes and benefits are presented (Botti and McGill, 2011; Kivetz and Zheng, 2017).

Consumers use different criteria for evaluating hedonic versus utilitarian products. They typically evaluate hedonic products by using subjective criteria, which involve feelings and emotions (Botti and McGill, 2011; Spiller and Belogolova, 2016), whereas they evaluate utilitarian products by using more objective and rational criteria, such as factual pieces of information about a product's quality or performance (Babin et al., 1994). Consequently, preferences for hedonic products would vary greatly among consumers, whereas those for utilitarian products tend to be more homogeneous as they are normally based on a few objective quality standards (Spiller and Belogolova, 2016).

We reason that these differences in evaluation criteria might influence consumers' reliance on either AI or human recommenders. More specifically, we posit that the focus on the subjective criteria for hedonic products favors suggestions provided by human recommenders, while the objective criteria used for utilitarian purchases make AI recommenders, at the very least, as effective at providing persuasive recommendations as humans. This reasoning aligns with prior research illustrating that AI recommenders lack emotional abilities, and thus are less effective than humans at subjective tasks and emotion-oriented jobs (Castelo et al., 2019a; Waytz and Norton, 2014). On the other hand, AI recommenders possess cognitive abilities, and thus might be as effective as human agents at objective and cognition-oriented tasks (Castelo et al., 2019a; Waytz and Norton, 2014).

Based on the foregoing, we predict that, for hedonic products, human recommenders will be more effective than AI recommenders at influencing consumers' reactions toward the recommended product, in terms of product attitude and purchase intention. Then again, for utilitarian products, recommendations from human and AI recommenders will not significantly differ in their influence on consumers' reactions toward the recommended products. Thus, we formulate the following hypothesis:

H1: Product type moderates the influence of recommender type on consumers' reactions toward the recommended product. Specifically, recommendations provided by human (vs. AI) recommenders generate more favorable reactions in consumers when the recommended products are hedonic (vs. utilitarian).

2.3 Mediating roles of mentalizing and self-referencing

Mentalizing refers to individuals' ability to infer the internal states of other actors and to understand those mental states (Frith and Frith, 2006; Van Overwalle and Baetens, 2009). This fundamental skill helps individuals to better understand how others feel and think, which is essential for well-functioning interpersonal relationships. For instance, it enables individuals to comprehend the intentions behind others' behavior. Some research suggests that mentalizing is also essential for the effective processing of product recommendations (Faraji-Rad et al., 2015). Notably, understanding a recommender's mental states could help the receiver feel more confident about the recommendation and whether it is provided in the best interest of the receiver. In such a way, mentalizing may contribute to explaining the source-related differences in recommendation effectiveness. In addition, we suggest that mentalizing might also contribute to another important function in the processing of recommendations: It could help consumers self-reference the information received through the recommendations.

Self-referencing refers to a cognitive process in which individuals associate self-relevant incoming information with personal needs to provide meaning to the incoming information (Debevec and Romeo, 1992). This process would typically lead to better learning and more favorable attitudes toward the newly acquired information (Burnkrant and Unnava, 1995). Self-referential thinking also increases the effectiveness of product recommendations (Xia and Bechwati, 2008), as it helps receivers predict how relevant a recommended product would be to their own needs (Yaniv et al., 2011). Indeed, such self-referential processing might be thought of as a form of surrogate experience with the product, which could help consumers envision the applications and benefits of the product in a consumption situation involving themselves (Dahl and Hoeffler, 2004). This should presumably make self-referencing a goal for consumers when reading product recommendations, and in particular when buying products based on subjective criteria such as for hedonic products.

Mentalizing presumably facilitates the process of self-referencing in the context of product recommendations. Neuroscience research suggests that similar brain areas are involved in understanding others' and one's own mental states (Böckler et al., 2017), and that taking another person's perspective to understand how they think could help people understand themselves better (Pfeifer et al., 2009; Saxe et al., 2006). This notion is supported by research in the marketing domain demonstrating that taking the perspective of another consumer would activate a self-referencing process that involves thinking about one's own preferences (Hattula et al., 2015). This might happen because mentalizing involves mentally simulating the experiences of another person (Savaki, 2010). When engaging in such mental simulation, people would visualize the other person in hypothetical scenarios usually in the form of stories or narratives (Escalas, 2007). Such stories provide a more contextually detailed picture of the product and its benefits than what is explicitly communicated by the recommender, which helps consumers envision how they themselves would act and feel in a similar story (Krishnamurthy and Sujan, 1999). For instance, stories in the form of customer reviews may provide consumers with a better understanding of how a reviewer felt about a service experience, which helps the consumers formulate their own feelings when experiencing a similar consumption situation (Rouliez et al., 2019). This is supported by research on affective forecasting suggesting that consumers use knowledge of other people's feelings with a product to predict how they would feel if they used that product (Eggleston et al., 2015). Consistent with this line of reasoning, we suggest that, when receiving product recommendations, consumers engage in mentalizing to get a deeper sense of how the recommender felt and thought about the product, which in turn would help the consumers infer whether the product being recommended is relevant for themselves.

A necessary condition for mentalizing is that people perceive the recommender as an intentional entity, with the ability of having internal states (Wiese et al., 2017). Put differently, mentalizing is dependent on attributing the concept of a mind to others. Without a mind to access, there is no mental states to understand. The attribution of a mind to other humans is something people learn from an early age and, therefore, something that should occur automatically (Frith and Frith, 2006). Hence, when receiving a recommendation from a human, consumers should automatically try to access and understand the recommender's mental states. On the other hand, consumers should be more reluctant to perceive AI recommenders as entities with a mind (Gray and Wegner, 2012; Wiese et al., 2017); and, because AI recommenders are essentially perceived as mindless, they are difficult to mentalize. Indeed, consumers often struggle to understand how AI recommenders *think* when generating their recommendations (Aksoy et al., 2006; Yeomans et al., 2019). Thus, human recommenders should, in general, be easier to mentalize than AI recommenders.

Nonetheless, mentalizing is a goal-driven process that people might only engage in when they are sufficiently motivated (Faraji-Rad et al., 2015). The motivation to mentalize is triggered by expectations about possible gains from reading others' minds. When people lack the motivation to mentalize, they tend to overlook the minds of others (Epley et al., 2013). This may lead to likening another person to an AI-based algorithm (Castelo et al., 2019b). Accordingly, lacking the motivation to mentalize might diminish the perception of human recommenders as distinct from AI ones. While Faraji-Rad et al. (2015) suggest that a recommendation context should generally motivate mentalizing, we propose that such a motivation varies depending on the product being recommended. More specifically, recommendations regarding hedonic versus utilitarian products should presumably trigger a stronger motivation to mentalize. Given the subjective criteria consumers typically use to evaluate these products and the heterogenous preferences consumers have around them, consumers may be more motivated to read into the minds of the recommenders to relate the recommender's experience with the product to themselves and better understand whether the product being recommended is self-relevant.

We propose that these expected gains from reading into the recommender's mind motivate consumers to mentalize when the product being recommended is hedonic rather than utilitarian. Conversely, as consumers evaluate utilitarian products more objectively than hedonic products (Spiller and Belogolova, 2016), the utilitarian nature of the product being recommended might diminish such potential gains. Hence, consumers should feel less motivated to mentalize.

In summary, human recommenders should be easier to mentalize than AI recommenders. However, for mentalizing to occur, the process must be activated by a mentalizing goal. We propose that *self-referencing* is a goal that is activated when the product being recommended is hedonic rather than utilitarian, as this situation helps consumers better understand the product's personal relevance. Ultimately, self-referencing may lead to enhanced recommendation effectiveness, as processing information in a self-relevant manner should make the information more persuasive (Burnkrant and Unnava, 1995). Hence, we hypothesize:

H2a: The interaction effect of recommender type by product type on consumers' reactions toward the recommended product is mediated by consumers' ability to mentalize and their tendency to self-reference the recommendation.

H2b: When the recommended product is hedonic (vs. utilitarian), consumers who receive a recommendation from human (vs. AI) recommenders are more inclined to mentalize. Mentalizing, in turn, increases consumers' tendency to self-reference the recommended product, thus generating more favorable reactions in consumers.

2.4 Overcoming the resistance to AI-based recommendations for hedonic products

Our central prediction is that, compared to human recommenders, AI recommenders are less effective when recommending hedonic products because they are more difficult to mentalize, and this difficulty in turn makes it harder for consumers to self-reference the recommendation. However, some scholars (Epley et al., 2013; Waytz et al., 2010) suggest that nonhuman agents could trigger mind perceptions when they display human traits. Such mind perceptions might, for instance, be triggered when an AI agent have a human-like appearance (Gray and Wegner, 2012) or behave in a human manner (Wiese et al., 2017).

Most studies in consumer behavior literature suggest that humanizing AI recommenders generates more favorable consumer reactions to products and companies (Araujo, 2018; Castelo et al., 2019a; Pizzi et al. 2021). This effect should presumably be more pronounced when consumers are motivated to mentalize the recommender, as we assume is the case for hedonic products. We therefore expect that increasing human-likeness can make AI recommenders more effective at recommending hedonic products and thus increase the effectiveness of this type of recommenders for this type of products. Therefore, we hypothesize the following:

H3a: The effect predicted in H2a holds for humanized (vs. nonhumanized) AI recommenders.

H3b: When the recommended product is hedonic (vs. utilitarian), consumers who receive a recommendation from humanized (vs. nonhumanized) AI recommenders are more inclined to mentalize. Mentalizing, in turn, increases consumers’ tendency to self-reference the recommended product, thus generating more favorable reactions in consumers.

3. Overview of studies

We tested our hypotheses in three studies by using different product categories (laptops in Study 1, headphones in Study 2, and smartphones in Study 3) and different operationalizations of consumer reactions toward the recommended product (product attitude in Study 1, and purchase intention in Studies 2 and 3). Study 1 tested H1 by showing that the effectiveness of human versus AI recommenders varies depending on the hedonic versus utilitarian nature of the recommended product. The study specifically showed that human recommenders generate more positive attitudes toward the recommended product when this product is hedonic; whereas human and AI recommenders do not significantly differ in effectiveness when the recommended product is utilitarian. Study 2 revealed a similar effect by showing that human recommenders generate a greater intention to purchase the recommended product when this product is hedonic but not when it is utilitarian. Importantly, this study tested H2a and H2b by showing that this effect is mediated by mentalizing and self-referencing. Study 3 tested H3a and H3b by showing that, when the recommended product is hedonic, increasing the human-likeness of AI recommenders can increase their effectiveness on consumers' purchase intention.

4. Study 1

4.1 Methods

One hundred seventy-seven respondents (M_{Age} = 39.11 years, SD = 10.59; 44% females) were recruited from Amazon's Mechanical Turk (MTurk) to participate in the study in exchange for a monetary compensation. Participants were randomly assigned to one of four experimental conditions, according to a 2 (recommender type: human vs. AI) × 2 (product type: hedonic vs. utilitarian) between-subjects design.

Participants first answered questions about their gender and age. Then, they read a brief scenario in which they were asked to imagine they were planning to purchase a new laptop and were searching the Internet for information on laptops. Laptops were used as they possess both utilitarian and hedonic benefits (Chitturi et al., 2008); thus, they could be framed in our descriptions as a product that assured either hedonic or utilitarian benefits and, consequently, could be purchased for entertainment or practical reasons, respectively (Chitturi et al., 2008). Participants read they had stumbled on a recommendation for a laptop with a fictional brand name. Thus, they were presented with a recommendation that varied across the four experimental conditions, according to the manipulated factors (i.e., recommender type and product type).

We manipulated recommender type by varying the recommendation source. Participants in the human recommender condition saw a recommendation about a laptop that was seemingly provided by another consumer. Participants in this condition were explicitly told that the recommendation was provided by another person. Furthermore, they were shown a profile picture of the recommendation source that displayed a generic person icon, along with a person's generic name, which indicated the human nature of the source. To avoid potential gender-related confounding effects, the recommender's name was varied, such that participants in this condition saw a recommendation provided by a same-gender consumer, in accordance with a procedure suggested by Feick and Higie (1992). Participants in the AI recommender condition saw the same recommendation as that shown to their counterparts in the human recommender condition, except for being ostensibly provided by an AI-based agent. These participants were explicitly told that the recommendation was provided by an AI recommender and were shown a profile picture that portrayed the typical robotic head of an AI recommender agent (Appendix A).

We also manipulated product type by varying the recommendation content. Participants in the hedonic product condition were asked to imagine that they were planning to buy a new laptop that they would have used for entertainment purposes. Then, they saw a recommendation—provided by either a human or an AI recommender depending on the assigned recommender type condition—that emphasized how exciting the laptop's high performance and new features were when playing games and doing fun activities. Participants in the utilitarian product condition were asked to imagine that they were planning to buy a new laptop that they would have used for work purposes. Then, they saw a recommendation that emphasized how useful the laptop's high performance and new features were when working and doing analytical activities (Appendix A).

Afterwards, participants reported their attitude toward the recommended product using three items assessed on seven-point semantic differential scales (1 = bad/7 = good; 1 = unpleasant/7 = pleasant; 1 = unfavorable/7 = favorable; see MacKenzie and Lutz, 1989). This product attitude measure captured participants' reactions toward the product and served as our dependent variable.

It is worth noting that, while we manipulated recommender type by varying the recommendation source, which was an objective characteristic of the recommendation, we manipulated product type in a more subtle way, by varying the description of the product being recommended. Therefore, the effectiveness of the latter manipulation directly depended on how participants perceived the assigned product description. To check the effectiveness of this manipulation, we asked participants to answer two questions drawn from Chen et al. (2017). In answering the first question, participants indicated to what extent they perceived buying the recommended laptop to be representative of pleasure-oriented consumption (i.e., fun, experiential). In answering the second question, participants indicated to what extent they perceived buying the recommended laptop to be representative of goal-oriented consumption (i.e., something one buys to carry out a necessary function or task in one's life). Participants' answers to the two questions were reported on a seven-point rating scale (1 = not at all, 7 = extremely).

Finally, we collected data about participants' familiarity with the product category using an item assessed on a seven-point scale (1 = not familiar at all, 7 = very familiar), and their level of expertise with the product category using another item assessed on a seven-point scale (1 = very low, 7 = very high). These measures served as control variables in the analysis.

4.2 Results

An analysis of the manipulation-check scores confirmed that participants in the hedonic product condition perceived buying the recommended laptop as more representative of pleasure-oriented consumption ($M = 5.55$, $SD = 1.21$), when compared to their counterparts in the utilitarian product condition ($M = 3.62$, $SD = 1.61$), $F(1, 175) = 80.62$, $p < 0.001$. Conversely, participants in the utilitarian product condition perceived buying the recommended laptop as more representative of goal-oriented consumption ($M = 5.80$, $SD = 1.21$), when compared to their counterparts in the hedonic product condition ($M = 4.07$, $SD = 1.81$), $F(1, 175) = 55.96$, $p < 0.001$. Thus, our product type manipulation was successful.

To test H1, we first averaged the scores obtained for the three items assessing product attitude (Cronbach $\alpha = 0.94$) to constitute an aggregate measure of the construct. Thus, we conducted a two-way ANCOVA that expressed product attitude as a function of recommender type (human vs. AI), product type (hedonic vs. utilitarian), and their interaction, with participants' familiarity and expertise with the product category serving as covariates. The analysis revealed a significant main effect of recommender type, such that participants in the human recommender condition exhibited a more favorable attitude toward the recommended product ($M = 5.65$, $SD = 0.99$) compared to those in the AI recommender condition ($M = 5.28$, $SD = 1.08$), $F(1, 171) = 5.96$, $p = 0.02$.

More importantly, the analysis revealed a significant interaction effect between the two manipulated factors, $F(1, 171) = 3.83$, $p = 0.05$. Consistent with H1, when the recommended laptop was framed as a hedonic product, participants reported a more favorable product attitude if the recommendation was provided by a human recommender (*M* = 5.80, *SD* = 0.93) rather than an AI recommender (*M* = 5.10, *SD* = 1.09), *t*(173) = 3.19, *p* = 0.002. In contrast, when the laptop was framed as a utilitarian product, participants' product attitude did not vary significantly as a function of whether the recommender was human (*M* = 5.50, *SD* = 1.04) or AI-based (*M* = 5.46, *SD* = 1.05), *t*(173) = 0.19, *p* = 0.85 (see Fig. 2).

[Insert Figure 2 about here]

5. Study 2

Study 2 tested H2a and H2b by providing evidence for the mediating role of mentalizing and self-referencing in the interaction effect of recommender type and product type.

5.1 Methods

One hundred and ninety-five respondents (M_{Age} = 35.24 years, *SD* = 10.56; 39% females) were recruited from MTurk to participate in the study for a monetary compensation. As in Study 1, Study 2's participants were randomly assigned to one of four experimental conditions, according to a 2 (recommender type: human vs. AI) × 2 (product type: hedonic vs. utilitarian) between-subjects design.

After responding to the same demographic questions as in Study 1, participants were presented with one of four different scenarios that manipulated both recommender type and product type as in Study 1. The four scenarios were similar to those developed in Study 1, except that headphones were the recommended product instead of laptops. Headphones indeed are a product that could be used for both utilitarian and hedonic purposes and has been employed in previous research (Choi et al., 2014).

Regarding the recommender type manipulation, participants in the human recommender condition saw a recommendation about a pair of headphones that was seemingly provided by another consumer. They were told that the recommender was another person, and they were shown a profile picture that displayed a generic person icon, along with a person's generic name, which was varied to assure that participants were presented with a same-gender recommender. In contrast, participants in the AI recommender condition saw the same recommendation as that employed in the human condition, except for being ostensibly provided by an AI recommender. Here, participants were told that the recommender was an intelligent virtual agent based on AI, and they were shown a profile picture that portrayed a typical robotic head (Appendix B).

Regarding the product type manipulation, participants in the hedonic product condition were asked to imagine that they were planning the purchase of a new pair of headphones that they would use for entertainment purposes. Then, they saw a recommendation for a pair of headphones with high sound quality and great noise cancellation that could make playing computer games and listening to music very enjoyable. In contrast, participants in the utilitarian product condition were asked to imagine that they were planning the purchase of a new pair of headphones that could help them increase their focus when working. Then, they saw a recommendation for a pair of headphones with high sound quality and great noise cancellation that could help them clear away noisy distractions at the workplace.

After reading the assigned scenario and recommendation, participants were asked to rate their intention to purchase the recommended pair of headphones using two items regarding their likelihood of purchasing the product and their interest in purchasing the product, which were adapted from Jiang et al. (2010) and assessed on seven-point scales (1 = very unlikely/not interested at all, 7 = very likely/very interested).

Next, we measured the two process-related variables regarding mentalizing and self-referencing. Mentalizing was assessed using two items drawn from Faraji-Rad et al. (2015) (i.e., "I feel I understand how the recommender thinks about the product", "I can understand how the sender feels when using that product"); self-referencing was assessed using three items drawn from Debevec and Romeo (1992) and Escalas (2007) (i.e., "The message related to me personally", "The message made me picture myself trying the product", "The message was personally relevant to me"). The two items regarding mentalizing and the three items regarding self-referencing were assessed on seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Finally, participants answered the same manipulation-check questions and rated their familiarity and expertise with the product category as in Study 1.

5.2 Results

Participants in the hedonic product condition perceived buying the recommended pair of headphones as more representative of pleasure-oriented consumption (M = 5.88, SD = 1.05), when compared to their counterparts in the utilitarian product condition (M = 4.73, SD = 1.46), $F(1, 193) = 39.45$, $p < 0.001$. In contrast, participants in the utilitarian product condition perceived buying the recommended pair of headphones as more representative of goal-oriented consumption (M = 5.34, SD = 1.54), when compared to their counterparts in the hedonic product condition (M = 4.10, SD = 1.88), $F(1, 193) = 25.38$, $p < 0.001$.

To test H2a and H2b, we averaged the two items regarding participants' purchase intention ($r = 0.86$, $p < 0.001$) to constitute an aggregate measure of the construct. This measure served as the dependent variable in the analysis. We also averaged the two items assessing mentalizing ($r = 0.78$, $p < 0.001$) and the three items assessing self-referencing (α = 0.88) to constitute aggregate measures of the respective constructs, which served as sequential mediators. Next, we conducted a moderated serial mediation analysis using the SPSS PROCESS macro (Model 86; Hayes, 2018), with 5,000 bootstrapping samples. The model included recommender type (coded as a binary variable, taking the values -1 for the AI recommender and 1 for the human recommender) as the independent variable, mentalizing and self-referencing as the serial mediators, and purchase intention as the dependent variable. Product type (coded as a binary variable, taking the values -1 for the utilitarian product and 1 for the hedonic product) served as the moderator of the relationship between recommender type and mentalizing. Both respondents' familiarity and expertise with the product category served as covariates.

The statistical analysis was conducted in four steps. In the first step, mentalizing was regressed on recommender type, product type, and their interaction, while controlling for the two covariates. The obtained results showed a main effect of recommender type on mentalizing that was positive and significant ($b = 0.28$, $t(189) = 3.59$, $p < 0.001$). More importantly, there was a significant interaction effect between recommender type and product type on mentalizing ($b = 0.16$, $t(189) = 2.07$, $p = 0.04$). Consistent with our prediction, the estimated effects of recommender type on mentalizing conditioned on the type of product being recommended revealed that participants were more inclined to mentalize when the recommender was human rather than AI-based; however, this effect was significant when the product being recommended was hedonic ($b = 0.44$, $t(189) = 4.00$, $p < 0.001$) and nonsignificant when the product was utilitarian ($p = 0.28$).

In the second step of the analysis, self-referencing was regressed on mentalizing and recommender type, while controlling for the two covariates. The obtained results showed that mentalizing exerted a significant and positive effect on self-referencing ($b = 0.58$, $t(190) = 8.04$, $p < 0.001$), while the effect of recommender type was nonsignificant ($p = 0.88$). This result indicated that participants with a higher propensity to infer the recommender's mental states were more likely to regard the recommended product as self-relevant.

In the third step, participants' purchase intention was regressed on self-referencing, mentalizing, recommender type, product type, and the interaction between the latter two variables, while controlling for the two covariates. The results revealed a significant and positive effect of self-referencing on purchase intention ($b = 0.64$, $t(187) = 9.95$, $p < 0.001$), along with a significantly positive effect of mentalizing ($b = 0.31$, $t(187) = 4.11$, $p < 0.001$), while the effect of recommender type was nonsignificant ($p = 0.74$). These results suggested that higher levels of mentalizing and self-referencing were associated with a greater intention to purchase the recommended product. Further, this step of the analysis revealed a nonsignificant interaction effect between recommender type and product type on purchase intention ($p = 0.63$). This result indicated that the interaction effect between the two manipulated factors is fully mediated by mentalizing and self-referencing.

In the fourth step of this analytical procedure, we implemented the aforementioned bootstrapping estimation method to detect the indirect effects. The analysis showed that the interaction between recommender type and product type exerted an indirect effect on purchase intention via mentalizing ($b = 0.10$, 95% confidence interval [CI] = 0.004, 0.23). To probe the nature of such an interactive indirect effect, we estimated the indirect effect of recommender type on purchase intention within the hedonic and utilitarian product conditions. The results showed that the human (vs. AI) nature of the recommender increased participants' purchase intention because of their increased propensity to read into the minds of the recommender. However, this indirect effect was significant when the recommended product was hedonic ($b = 0.14$, 95% CI = 0.04, 0.26) and nonsignificant when the product was utilitarian (95% CI included zero).

More importantly, the analysis revealed a significant indirect effect of the aforementioned interaction term on purchase intention via both mentalizing and self-referencing ($b = 0.12$, 95% CI = 0.004, 0.25). This provides support for H2a. To explore the nature of this serially mediated interactive effect on the dependent variable, we estimated the indirect effect of recommender type on purchase intention for each of the two types of products. As predicted in H2b, when the recommended product was hedonic, the human (vs. AI) nature of the recommender increased the participants' purchase intention via an increase in both participants' propensity to mentalize and tendency to regard the recommended product as self-relevant (b = 0.16, 95% CI = 0.07, 0.29). Conversely, when the recommended product was utilitarian, this indirect effect of recommender type on purchase intention via the two serial mediators was nonsignificant (95% CI included zero) (see Fig. 3).

[Insert Figure 3 about here]

6. Study 3

Study 3 tested H3a and H3b, which predict that humanizing AI recommenders should enhance mentalizing, thus leading to increased self-referencing and more positive consumer reactions. In this study we tested the same moderated-mediation model as in Study 2, except that in this study we focused on the AI recommender type. Indeed, we used either a humanized or nonhumanized AI recommender. In accordance with previous research (Araujo, 2018, Kim et al., 2019b), we manipulated human-likeness by changing the appearance and name of the recommender.

6.1 Methods

Two hundred and forty-five respondents (M_{Age} = 38.58 years, SD = 11.74; 41% females) were recruited from MTurk to participate in the study for a monetary compensation. They were randomly assigned to one of four experimental conditions, according to a 2 (AI recommender type: humanized vs. nonhumanized) × 2 (product type: hedonic vs. utilitarian) between-subjects design.

After responding to the same demographic questions as in Studies 1 and 2, participants were presented with one of four scenarios that manipulated both AI recommender type and product type. The four scenarios were similar to those employed in Studies 1 and 2, except that smartphones were the recommended product. Smartphones indeed are a product that could be used for both utilitarian and hedonic purposes and has been employed in previous research (Chitturi et al., 2008).

Regarding the AI recommender type manipulation, participants in the humanized AI recommender condition saw a recommendation about a smartphone that was provided by an AI recommender with a human-like appearance and name. They were also told that the recommender was a human-like virtual agent based on AI. In contrast, those in the nonhumanized AI recommender condition saw the same recommendation, except for being provided by a recommender with a robot-like appearance and name, which were identical to those used in Studies 1 and 2. Here, participants were told that the recommender was a virtual agent based on AI (Appendix C). As in Studies 1 and 2, we varied the human-like appearance and name of the AI recommender to assure that respondents were presented with same-gender recommender agents.

Regarding the product type manipulation, participants in the hedonic product condition were asked to imagine that they were planning the purchase a new smartphone that they would use for entertainment purposes. Then, they saw a recommendation for a smartphone with features that were very entertaining and exciting when doing fun activities. In contrast, participants in the utilitarian product condition were asked to imagine that they were planning the purchase a new smartphone that could be used for work purposes. Then, they saw a recommendation for a smartphone with features that were very useful when working or doing other practical tasks.

After reading the assigned scenario and recommendation, participants were asked to rate their intention to purchase the product using three items assessed on seven-point semantic differential scales (i.e., 1 = unlikely/7 = likely; 1 = definitely would not/7 = definitely would; 1 = improbable/7 = probable; see Ko et al., 2005). Next, participants rated the degree of mentalizing and self-referencing, using the same items as in Study 2, and answered the same manipulation-check questions and covariate measures as in the previous two studies.

6.2 Results

Participants in the hedonic product condition perceived buying the smartphone as more representative of pleasure-oriented consumption ($M = 5.37$, $SD = 1.39$), when compared to their counterparts in the utilitarian product condition ($M = 4.22$, $SD = 1.75$), $F(1, 243) = 31.87$, $p < 0.001$. In contrast, participants in the utilitarian product condition perceived buying the smartphone as more representative of goal-oriented consumption ($M = 5.38$, $SD = 1.36$), when compared to their counterparts in the hedonic product condition ($M = 4.64$, $SD = 1.84$), $F(1, 243) = 12.72$, $p < 0.001$.

To test H3a and H3b, we averaged the three items assessing participants' purchase intention ($\alpha = 0.96$), the two items assessing mentalizing ($r = 0.79$, $p < 0.001$), and the three items assessing self-referencing ($\alpha = 0.93$) to constitute aggregate measures of the respective constructs. Next, we conducted a moderated serial mediation analysis using the same procedure as in Study 2. The model included type of AI recommender (coded as a binary variable, taking the values -1 for the nonhumanized recommender and 1 for the humanized recommender) as the independent variable, mentalizing and self-referencing as the serial mediators, and purchase intention as the dependent variable. Product type (coded as a binary variable, taking the values -1 for the utilitarian product and 1 for the hedonic product) served as the moderator of the relationship between AI recommender type and mentalizing. Both participants' familiarity and expertise with the product category served as covariates.

Following the same analytical approach as in Study 2, mentalizing was first regressed on AI recommender type, product type, and their interaction, while controlling for the two covariates. As predicted, the results revealed a significant interaction effect between AI recommender type and product type on mentalizing ($b = 0.20$, $t(239) = 2.04$, $p = 0.04$). In particular, the estimated effects of AI recommender type on mentalizing conditioned on the type of product being recommended revealed that participants were more inclined to mentalize when the AI recommender was humanized rather than nonhumanized; however, this effect was significant when the product being recommended was hedonic ($b = 0.30$, $t(239) = 2.12$, $p = 0.03$) and nonsignificant when the product was utilitarian ($p = 0.46$).

In the second step of the analysis, self-referencing was regressed on mentalizing and AI recommender type, while controlling for the two covariates. As in Study 2, the obtained results showed that mentalizing exerted a significant and positive effect on self-referencing ($b = 0.74$, $t(240) = 13.09$, $p < 0.001$), while the effect of AI recommender type was nonsignificant ($p = 0.90$).

In the third step, participants' purchase intention was regressed on self-referencing, mentalizing, AI recommender type, product type, and the interaction between the latter two variables, while controlling for the two covariates. The results revealed a significant and positive effect of self-referencing ($b = 0.71$, $t(237) = 13.01$, $p < 0.001$), while the effects of mentalizing ($p = 0.69$) and AI recommender type ($p = 0.23$) were nonsignificant. These results suggested that higher levels of self-referencing were associated with a greater intention to purchase the recommended product. Further, this step of the analysis revealed a nonsignificant interaction effect between AI recommender type and product type on purchase intention ($p = 0.45$). This result indicates that this interaction effect is fully mediated by mentalizing and self-referencing.

In the fourth step of the analysis, we implemented the bootstrapping estimation method to detect the indirect effects. The analysis showed that the interaction between AI recommender type and product type exerted an indirect effect on purchase intention via both mentalizing and self-referencing ($b = 0.21$, 95% CI = 0.02, 0.41), providing support for H3a. To explore the nature of this serially mediated interactive effect on the dependent variable, we estimated the indirect effect of the recommender type on purchase intention within each of the two product conditions. As predicted in H3b, when the recommended product was hedonic, the humanized (vs. nonhumanized) AI recommender increased participants' purchase intention via an increase in both participants' propensity to mentalize and tendency to regard the recommended product as self-relevant ($b = 0.15$, 95% CI = 0.01, 0.30). Conversely, when the recommended product was utilitarian, this indirect effect of recommender type on purchase intention via the two serial mediators was nonsignificant (95% CI included zero) (see Fig. 4).

[Insert Figure 4 about here]

7. General discussion

In the present research, we empirically compared the effectiveness of human and AI recommenders to show *when* and *why* consumers rely on each of them. Across three experimental studies, we showed that consumers react more favorably to human (vs. AI) recommenders, and thus express better product attitudes and higher purchase intentions, when the recommended products are hedonic rather than utilitarian. This effect was robust across different products (i.e., laptops, headphones, and smartphones) and measures of consumer reactions toward the recommended products (i.e., product attitude and purchase intention). More importantly, in Study 2, we provided evidence for a critical mechanism underlying this effect, by showing that the human recommenders' greater effectiveness at influencing consumers' reactions toward hedonic products depends on the degree to which this type of recommender enables receivers to mentalize and then to self-reference. Finally, in Study 3, we showed that consumers' reluctance to rely on AI recommenders in the hedonic product context could be reduced by humanizing these recommenders.

7.1 Theoretical implications

Our findings contribute to existing literature in three primary ways. Firstly, whereas previous research has shown that the relative effectiveness of human versus AI recommenders may vary depending on the hedonic versus utilitarian nature of recommended products (Longoni and Cian, 2020), our findings delve deeper into this phenomenon by elucidating a fundamental process underlying the differential effectiveness of these two types of recommenders. In particular, we found that the enhanced effectiveness of human recommenders in the hedonic product context is mediated by consumers' ability to mentalize and their subsequent tendency to self-reference. This finding expands current understanding of how and why human and AI recommenders differ in influencing consumers' reactions, beyond consumers' beliefs about how competent and effective different types of recommenders are in providing different recommendations (Castelo et al., 2019a; Longoni and Cian, 2020). Indeed, while such beliefs are likely to change as consumers' experience with AI recommenders increases, their increased ability to mentalize with human (vs. AI) recommenders should be more stable as this process is rooted in fundamental neural responses (Frith and Frith, 2006).

Furthermore, whereas prior explanations based on consumers' competence and effectiveness perceptions ultimately relate to how trustworthy consumers find the different recommenders (Castelo et al., 2019a), our suggested process relates to how such recommenders shape consumers' understanding of the recommendations. In particular, we suggest that human (vs. AI) recommenders – by triggering mentalizing responses – may provide consumers with cues about their personal experiences with the product being recommended beyond what they write in the recommendations. These cues may help consumers infer a product's personal relevance. Hence, we offer an alternative to the traditional notion that a recommender's influence is a function of trust-related source characteristics such as competence, trustworthiness, and attractiveness (Ohanian, 1990). Rather, we suggest that the enhanced influence of human (vs. AI) recommenders depends on how these recommenders facilitate message comprehension.

Secondly, while prior research on mentalizing suggests that mind perception is central in differentiating humans from robots (Gray and Wegner, 2012; Wiese et al., 2017), our research is the first to demonstrate the usefulness of this theory in a consumer context. In particular, we showed that mentalizing could be essential in distinguishing humans from AI recommenders in a product recommendation context. In doing so, we extend the research by Faraji-Rad et al. (2015), which suggests that a product recommendation context should generally activate mentalizing. Our findings contribute to this stream of research by showing that mentalizing is primarily triggered when humans are recommending hedonic products. Hence, our findings align with the notion that people engage in mentalizing when it seems useful for achieving particular goals (Epley et al., 2013). We suggest that self-referencing is such a goal, which is triggered when consumers need to understand whether a hedonic product fits with their individual tastes. When the product could be evaluated based on more objective criteria, though, there should be less to gain from self-referencing (Spiller and Belogolova, 2016). Accordingly, our findings indicate that self-referencing might indeed be the goal that motivates consumers to mentalize with human recommenders in the hedonic product condition; however, they also show no difference in mentalizing between human and AI recommenders in the utilitarian product condition.

Thirdly, by building on research on anthropomorphism (Blut et al., 2021), we showed that humanizing AI recommenders could elicit mentalizing and self-referencing responses in consumers, and thereby enhance their positive reactions toward the recommended products, when such products are hedonic (vs. utilitarian). This finding adds to the debate on whether providing AI recommenders with human-like features is beneficial or not (Mende et al., 2020). While some scholars suggest that humanized AI recommenders should generate more positive reactions in consumers (Araujo, 2018; Castelo et al., 2019a; Pizzi et al. 2021), other researchers suggest that these AI recommenders are likely to elicit aversive responses in consumers (Fernandes and Oliveira, 2021; Kim et al., 2019b). Our findings give support to the former research stream, suggesting that companies could benefit from increasing the human-likeness of AI recommenders. Nonetheless, the positive effect of humanizing AI recommenders is only present in the hedonic condition, providing support to previous research suggesting that human-like features may be more relevant for emotionally complex, highly customized settings (Wirtz et al., 2018).

7.2 Managerial implications

With the development of AI, marketers have access to increasingly smart online recommendation systems. Given these recommendation systems' potential to help consumers with highly accurate advice (Yeomans et al., 2019), marketers might be tempted to adopt solely that type of recommenders, at the expense of human recommenders. Our findings show that AI recommenders could indeed influence consumers' decisions. However, there is a limitation to this type of recommender. When compared to human recommenders, AI recommenders are less effective for hedonic products. Therefore, marketers should take the product type (hedonic vs. utilitarian) into consideration before deciding upon which type of recommenders to use in their online promotional strategy.

However, our findings also show that, by undertaking certain actions, marketers may overcome this limitation, and thus reduce consumers' aversion against AI recommenders in the hedonic product context. Specifically, giving AI recommenders a human-like appearance and name could increase the persuasiveness of this type of recommenders, which could thus become an effective source of influence in the marketing of hedonic products. In addition, the distinction between hedonic and utilitarian products could be framed based on emphasizing certain product benefits and consumption motives (Botti and McGill, 2011; Kivetz and Zheng, 2017). Accordingly, either recommender type might be effective in recommending a same product, depending on how the product is presented in the recommendation message. For instance, an AI recommender might still be effective in recommending a primarily hedonic product (e.g., designer clothes) (Dhar and Wertenbroch, 2000), if the provided recommendation focuses on utilitarian aspects of the product (e.g., fabric type, durability). Consequently, marketers could employ AI recommenders successfully for more hedonic products by programming these recommenders to focus on utilitarian aspects of these products. However, companies offering products that are predominately consumed for hedonic purposes (e.g., books, music, movies) should presumably benefit more from human rather than AI recommenders.

7.3 Limitations and future research

Our findings have limitations that offer opportunities for future research. Firstly, they derived from participants' self-report measures of product attitude and purchase intention. Future studies could try to replicate our results using more behavioral dependent variables. Secondly, we used a two-item scale to measure the mentalizing construct. While we acknowledge that using only two items to assess a construct is not ideal, we believe this did not undermine our findings, considering the robustness of our statistical results regarding the mediating process across Studies 2 and 3. However, future studies could adopt scales with three or more items to assess this construct.

Thirdly, our findings derive from experimental manipulations that only involved products from broader consumer electronics categories (i.e., laptops, headphones, smartphones). We selected such products both because they could be easily framed as either hedonic or utilitarian options and because they were successfully adopted in previous studies (Chitturi et al., 2008; Choi et al., 2014). However, we are cautious in generalizing our findings to other product categories or service contexts. In particular, consumers' reactions to human versus AI recommenders might be different in a service context, in which purchases often are perceived as riskier and more complex (Wirtz et al., 2018). Such a type of purchases might indeed increase consumers' skepticism toward AI recommenders, potentially leading to "algorithm aversion" even for services of a more utilitarian nature. Future studies could delve deeper into this interesting aspect.

Fourthly, our manipulation of human-likeness only varied AI recommenders' appearance and name. However, with the development of AI technology, these recommenders could imitate humans in several other ways, such as using a human voice (Fernandes and Oliveira, 2021) or performing human-like movements (Castelo et al., 2019a). Future studies could therefore test whether these aspects influence consumers' perception of AI recommenders and their reactions toward different types of recommended products. Another avenue for future research is to examine other source characteristics that might contribute to explaining differences between human and AI recommenders in their ability to influence consumers' reactions toward the recommended products. These characteristics could include credibility aspects, such as a recommender's attractiveness, trustworthiness, and competence (Ohanian, 1990).

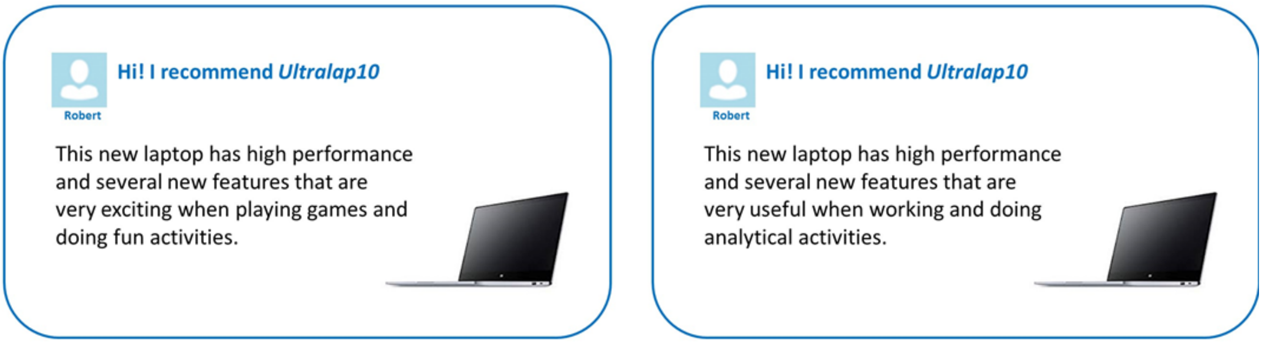
Finally, while our findings indicate that consumers perceive human recommenders as more helpful in providing personally relevant advice with special regard to hedonic products, in reality AI recommenders could be better at providing advice that reflect consumers' individual preferences (Yeomans et al., 2019). This discrepancy between perception and reality creates a suboptimal situation for consumers, whereby consumers may rely more on recommenders that are less capable of providing personalized advice. Future studies could examine how marketers could increase the perceived helpfulness of AI recommenders, thereby reducing the resistance against these recommenders.

Appendix A

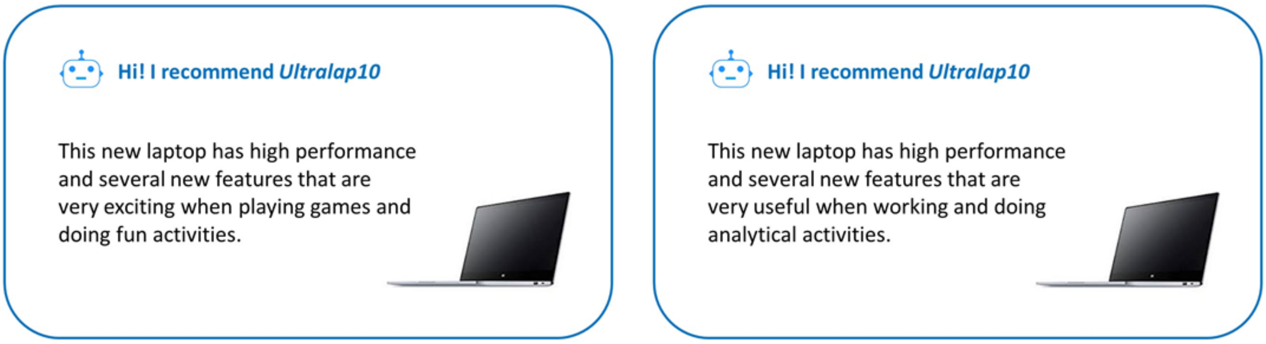
Study 1 - Scenario:
Imagine you are planning to buy a new laptop that you would use for *entertainment purposes such as playing games and watching movies* (hedonic product condition)/*work purposes such as writing documents and doing analytical tasks* (utilitarian product condition). To make the best possible decision, you search the Internet for information regarding laptops. During your

search, you stumble on a recommendation from *another consumer* (human recommender condition)/*virtual agent based on artificial intelligence* (AI recommender condition) who reported the following:

Human recommender condition for the hedonic (left) versus utilitarian (right) product



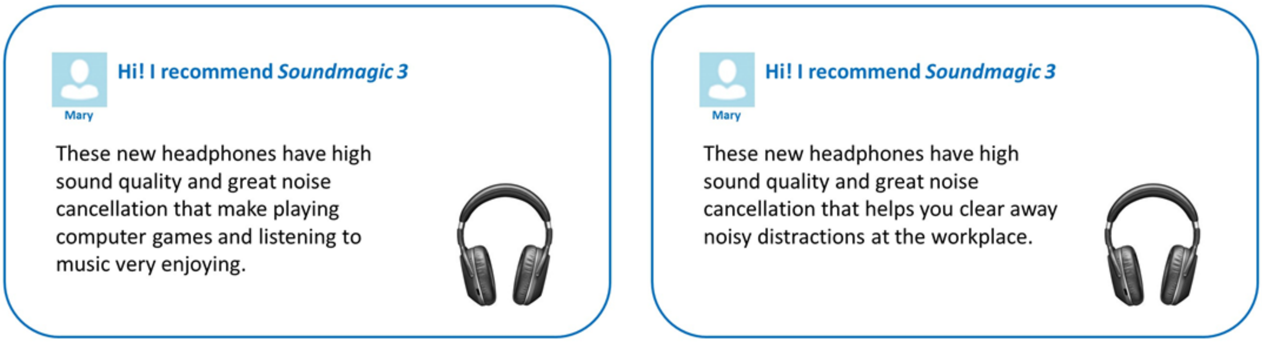
AI recommender condition for the hedonic (left) versus utilitarian (right) product



Appendix B

Study 2 - Scenario:
Imagine you are planning to buy a new pair of headphones that *you would use for entertainment purposes such as listening to music and playing computer games* (hedonic product condition)/*could help you increase your focus when working by cancelling out disturbing noises at your workplace* (utilitarian product condition). To make the best possible decision, you search the Internet for information regarding headphones. During your search, you stumble on a recommendation from *another consumer* (human recommender condition)/*virtual agent based on artificial intelligence* (AI recommender condition) who reported the following:

Human recommender condition for the hedonic (left) versus utilitarian (right) product

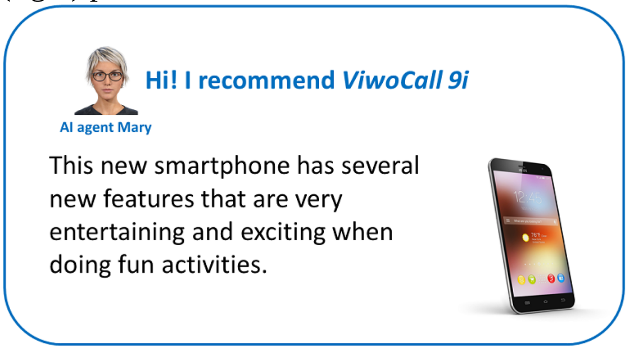


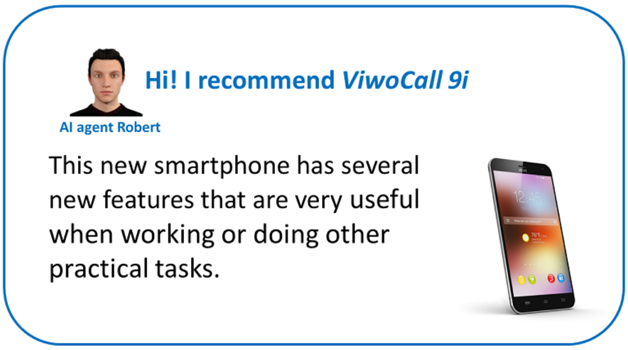
AI recommender condition for the hedonic (left) versus utilitarian (right) product

Appendix C

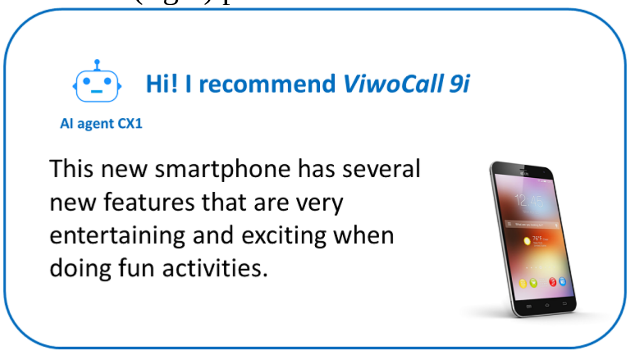
Study 3 - Scenario:
Imagine you are planning to buy a new smartphone that you would use for *playing games and other fun activities* (hedonic product condition)/*work and other practical tasks* (utilitarian product condition). To make the best possible decision, you search the Internet for information regarding smartphones. During your search, you stumble on a recommendation from a *human-like virtual agent based on artificial intelligence* (humanized AI recommender condition)/*virtual agent based on artificial intelligence* (nonhumanized AI recommender condition) who reported the following:

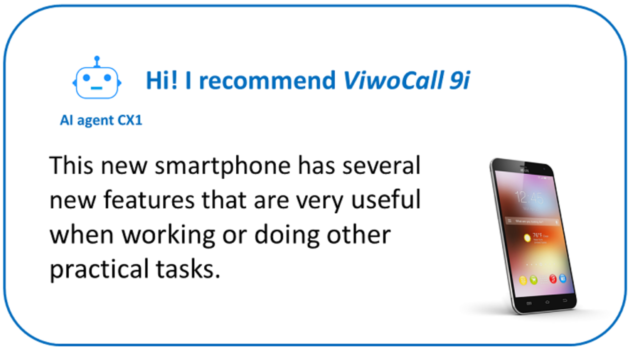
Examples of humanized AI recommenders employed for the hedonic (left) versus utilitarian (right) product*





Examples of nonhumanized AI recommenders employed for the hedonic (left) versus utilitarian (right) product





* The pictures displaying the two humanized AI recommenders were adopted from botlibre.biz, licensed under Creative Commons Attribution 3.0.

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Source	Method (Type of participants)	Main independent variable	Mediating mechanism	Main dependent variable	Main findings
Önkal et al. (2009)	Experiment (students)	Financial advice from human expert vs. statistical forecasting method	None	Influence of advice (how much participants adjusted their own forecast after receiving advice)	Human advice is more influential than algorithmic advice.
Diab et al. (2011)	Experiment (working adults)	Employee selection based on human evaluation vs. a mathematical algorithm	None	Perceived usefulness, fairness, and flexibility of selection method	Human evaluations are perceived as more useful, fair, and flexible than algorithm-based evaluations.
Waytz and Norton (2014)	Experiment (MTurk workers)	Cognition- vs. emotion-oriented jobs	Perceived emotion required for the job	Feeling of comfort in outsourcing jobs to human versus robots	People are less comfortable in outsourcing jobs to robots when the job is emotional (vs. cognitive) in nature because they believed such jobs required emotional skills.
Dietvorst et al. (2015)	Experiment (students and MTurk workers)	Observing vs. not observing an algorithm perform (and err) at forecasting tasks	Confidence in the source	Choice to rely on algorithm vs. oneself or algorithm vs. other participants when making incentivized forecasts	People rely less on an algorithm after seeing it errs, even when the algorithm outperforms humans. The effect is mediated by reduced confidence in the algorithm.
Yeomans et al. (2019)	Experiment (MTurk workers and museum visitors)	Receiving joke recommendations from either a human or an algorithm	Subjective understanding of the recommendation process	Preference for the recommendation source	People prefer to receive jokes from humans (vs. algorithms) because it is easier to understand how humans make recommendations.
Longoni et al. (2019)	Experiment (MTurk workers and students)	Receiving medical treatment from a human vs. an algorithm	Uniqueness neglect	Choice of and willingness to pay for medical provider	People prefer to receive medical treatment from humans because they think algorithms neglect their unique circumstances.
Castelo et al. (2019a)	Experiment (MTurk workers, Prolific workers, Facebook users)	Receiving advice from a human vs. an algorithm across subjective vs. objective tasks	Discomfort and perceived effectiveness	Trust in and preference for the advisor	People trust and rely less on algorithms for tasks that seem subjective (vs. objective) in nature because they are seen as less effective and less comfortable to use for such tasks.
Longoni and Cian 2020	Experiment (consumers, students and MTurk workers)	Receiving product recommendations from a human vs. AI recommender across hedonic and utilitarian product conditions	Competence perceptions	Product choice and choice of the recommender	Consumers rely more on recommendations from AI systems when the product is utilitarian, but rely more on recommendations from humans when the product is hedonic. The reason is that consumers perceive AI recommenders as more competent in the utilitarian realm and less competent in the hedonic realm.

Table 1. Previous research on the effectiveness of human versus AI recommenders

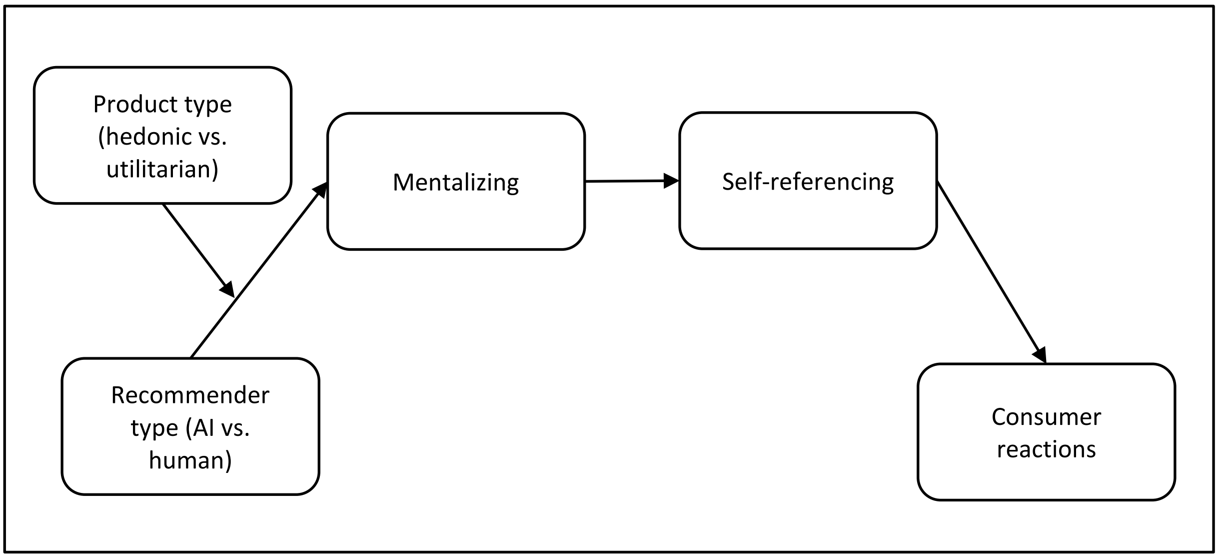
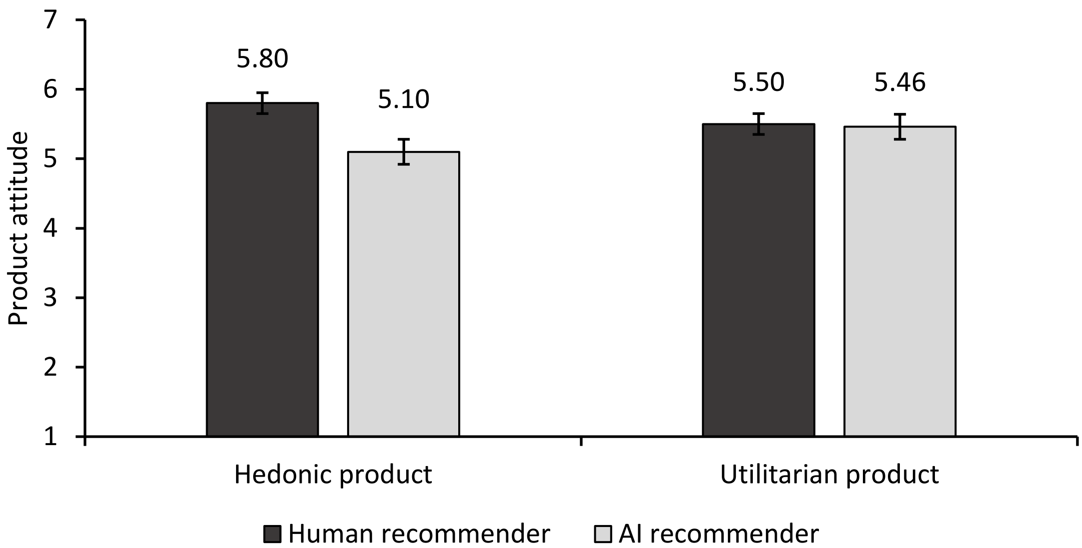
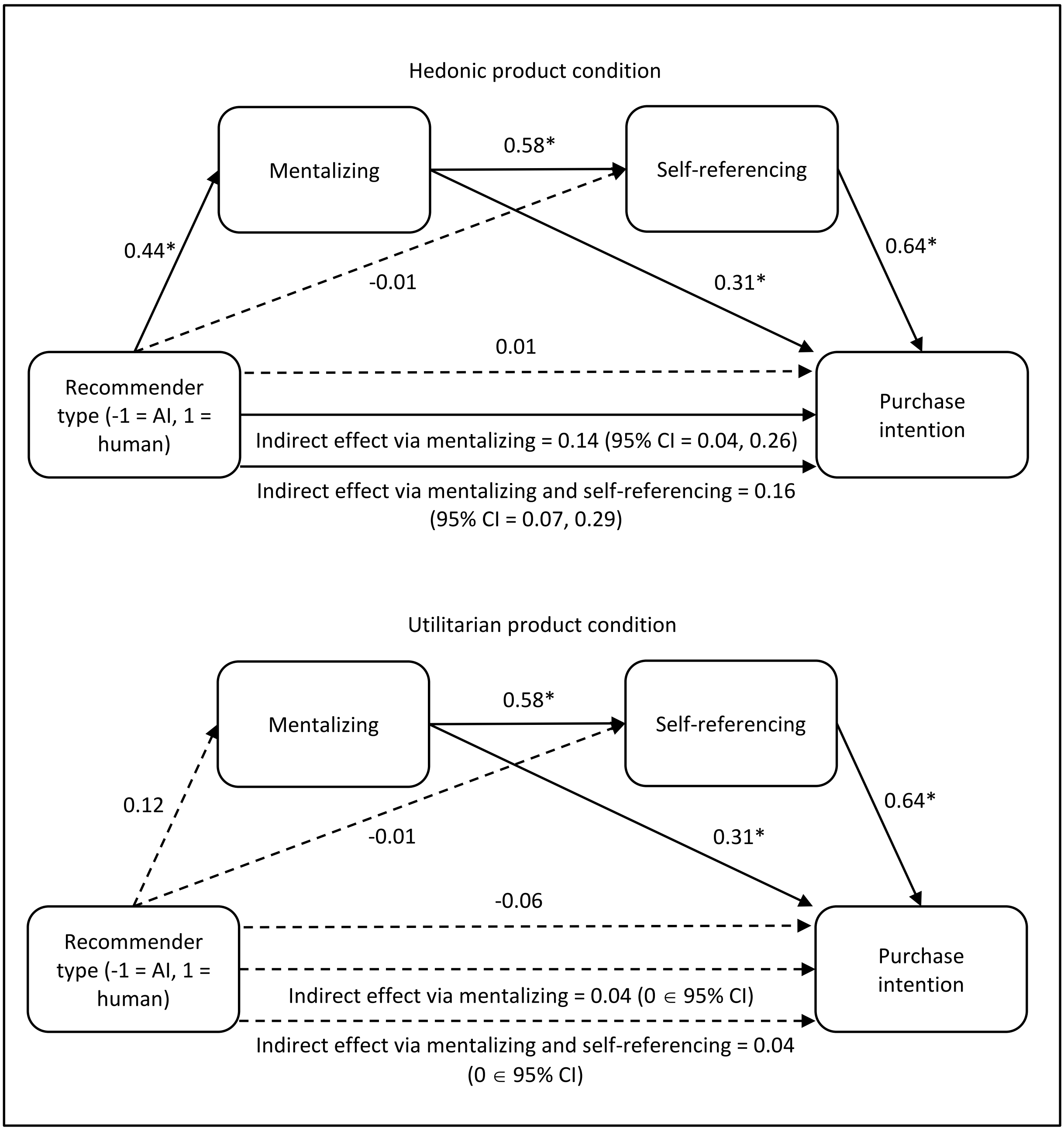


Fig. 1. The proposed moderated mediation model



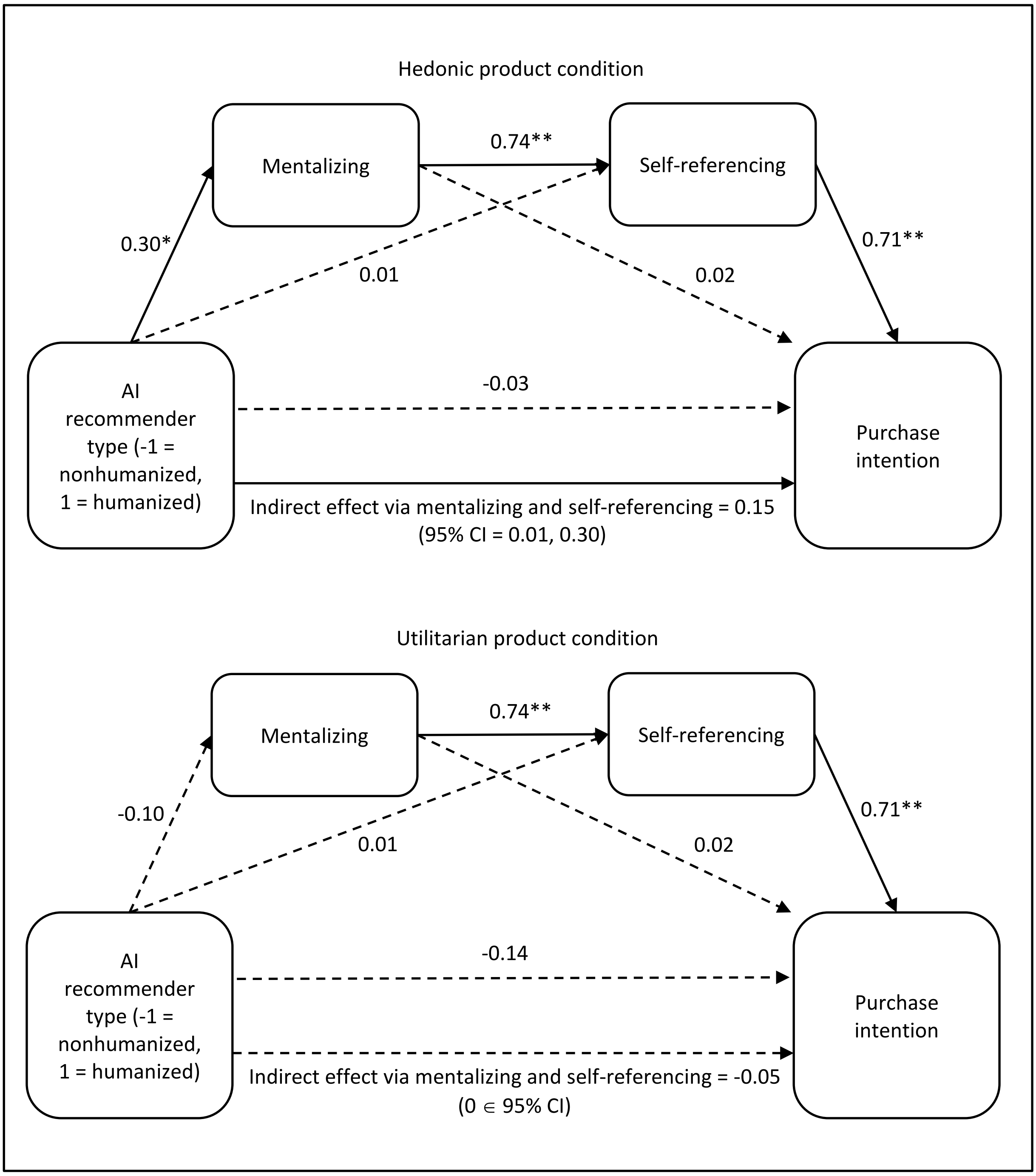
Error bars indicate standard errors.

Fig. 2. Product attitude as a function of recommender type and product type.



* $p < 0.001$. Arrows indicate direct effects, expect when they are explicitly denoted as indirect effects. Because the indirect effect of the interaction term (recommender type by product type) on purchase intention via self-referencing was nonsignificant ($b = -0.01$, $0 \in 95\%$ CI), the indirect effect of recommender type on purchase intention via self-referencing within the two product conditions were not estimated. Dotted arrows indicate nonsignificant effects.

Fig. 3. Conditional indirect effects of recommender type on purchase intention.



* $p < 0.05$; ** $p < 0.001$. Arrows indicate direct effects, expect when they are explicitly denoted as indirect effects. Because the indirect effects of the interaction term (recommender type by product type) on purchase intention via either mentalizing ($b = 0.01$, $0 \in 95\%$ CI) or self-referencing ($b = 0.01$, $0 \in 95\%$ CI) were nonsignificant, the indirect effects of recommender type on purchase intention via either mentalizing or self-referencing within the two product conditions were not estimated. Dotted arrows indicate nonsignificant effects.

Fig. 4. Conditional indirect effects of AI recommender type on purchase intention.