Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot?

Published Version:
Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? / Pizzi, G., Scarpi, D., Pantano, E.. - In: JOURNAL OF BUSINESS RESEARCH. - ISSN 0148-2963. - ELETTRONICO. - 129:(2021), pp. 878-890. [10.1016/j.jbusres.2020.11.006]

Availability:
This version is available at: https://hdl.handle.net/11585/782201 since: 2020-11-26

Published:
DOI: http://doi.org/10.1016/j.jbusres.2020.11.006

(Article begins on next page)

Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot?

Abstract

Advances in artificial intelligence provide new tools of digital assistance that retailers can use to support consumers while shopping. The aim of this research is to examine how consumers react as a function of assistants' appearance (human- vs. not human-like) and activation (automatic vs. human-initiated). We advance a model of sequential mediation whose empirical validation on 400 participants in two studies shows that non-anthropomorphic digital assistants lead to higher psychological reactance. In turn, reactance affects perceived choice difficulty, which positively reflects on choice certainty, perceived performance and—ultimately—satisfaction. Thus, although reactance might appear as a negative outcome, it eventually leads to higher satisfaction. Furthermore, initiation (system vs. user initiation) does not activate the chain of effects, but significantly interacts with anthropomorphism so that individuals exhibit lower reactance when confronted with human-like digital assistants activated by the consumer. Overall, reactance is highest for non-human like digital assistants that are computer-initiated.

Keywords. Artificial Intelligence; automation; chatbot; human-computer- interaction; consumer behavior

Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot?

1. Introduction

Many recent statistics show that companies claim to be using artificial intelligence (AI) and machine learning (ML) algorithms to solve a wide range of problems because they provide new tools for making accurate predictions and analyzing large data sets (Bertacchini, Bilotta, & Pantano, 2017; Murphy, Hofacker, & Gretzel, 2017; Pantano, Priporas, & Stylos, 2017). The advances in this direction make available new forms of interaction between consumers and firms while delivering innovative and better-customized services. However, the impact of AI in various industries needs further investigation (Huang & Rust, 2018). Specifically, the literature has highlighted the need to better understand the determinants of successful human–machine integrations and to ascertain whether AI- and ML-based technologies can provide valuable customer solutions consistently and with a service dominant logic perspective (Ng & Vargo, 2018; Vargo & Lusch, 2017). Indeed, there is an increasing awareness of the need to integrate consumers' perspective in developing new service systems to facilitate the value co-creation, and to contribute to the understanding of value co-creation (Edvardsson et al., 2011; Gustafsson et al., 2012; Peltier et al., 2020; Dahl et al., 2019). For instance, AI can be used to provide online customer assistance that transcends the traditional customized recommender systems. A meaningful example is the spreading of digital assistants, which might ultimately replace the salesforce and/or sales personnel in some activities such as the online management of relationships with customers (Mou & Xu, 2017; Huang & Rust, 2018). In particular, automated systems enable online interaction with consumers to help them during the online shopping experience (by showing new collections, suggesting new purchases, etc.) at a lower cost compared with the assistance provided by flesh-and-blood employees.

Digital assistants are nowadays being adopted in the luxury (e.g., Burberry or Louis Vuitton), apparel clothing (e.g., the Ted Baker “SeeMore” or Victoria Beckham “Messenger experience”), and tourism industries (e.g., St. James’s Hotel and Club, London). Despite their ability to manage many consumers requests simultaneously, digital assistants might influence consumers’ perceived control of the interaction, which might result in disappointment with the online recommendation (André et al., 2018) and/or the purchase decision (Lee & Lee, 2009). With this in mind, previous studies investigated the extent to which consumers are reluctant to get online personalized suggestions (recommendations), which results in negative consumer responses (Lee & Lee, 2009).

The aim of this research is to examine how consumers react when their choices are assisted by AI tools, by jointly addressing the assistant’s anthropomorphism and the locus of conversation initiation. Specifically, it aims to analyze whether and to what extent consumers develop psychological reactance as a function of the assistant’s appearance (level of anthropomorphism) and of whether it is activated automatically by the computer or spontaneously by the user. Furthermore, we aim to assess how reactance, in turn, affects consumers’ post-choice perceptions.

To this end, in this research we develop a sequential moderated mediation model that is tested empirically with a sample of 400 consumers in two studies by means of a between-subjects experimental design. Results overall support the hypothesized moderated mediation causal sequence, yielding an effect of the digital assistant’s anthropomorphism on consumer reactance, no effect of initiation (user vs. system), and an interaction between anthropomorphism and initiation. In turn, our results support that consumer reactance affects satisfaction via perceptions of choice difficulty, certainty, and perceived performance.

The paper is organized as follows: section 2 relates considerations from reactance theory (Brehm, 1966) and digital service assistance (Larivière et al., 2017) to individuals' perceptions of their decision-making process in a digital environment, combining these streams of literature into a comprehensive conceptual model. Sections 3 through 5 present and discuss the method and the results of the model estimation. In section 6, the implications for scholars and practitioners are discussed.

2. Theoretical background

Digital customer assistance includes several forms of automated tools such as recommender systems based on collaborative filtering (Mild & Reutterer, 2003; Mimoun, Poncin, & Garnier, 2012), content-based filtering (Felfernig, Friedrich, Jannach, & Zanker, 2006), and conversational agents (Araujo, 2018). Recommender systems "not only match and return every entry that matches the query but also emphasize relevance and usefulness and often individualize the information they present" (Gretzel & Fesenmaier, 2006, p. 81). Previous research has already shown that they are "very performing and seem to meet the expectations of users" (Mimoun et al., 2012, p. 616). Instead, conversational agents are "computer-generated graphically displayed entities that represent either imaginary characters or real humans controlled by artificial intelligence" (Choi, Miracle, & Biocca, 2001, p. 19) and differ from recommender systems in the degree of interaction and stimulation of social presence (McGinty & Smyth, 2006), which is significantly stronger for conversational agents (Choi et al., 2001). As a consequence, conversational agents have been found to be key to a sense of involvement (Heerink, Kröse, Evers, & Wielinga, 2010) and to potentially lead to higher levels of trust in the agents (Baier & Stüber, 2010; de Visser et al., 2017; Huang & Rust, 2018).

Accordingly, to understand the interaction between consumers and AI tools, the present research focuses specifically on conversational agents as forms of digital assistance.

2.1. Customer assistance and digital service assistance

Service automation is increasingly gaining scholarly attention in the retailing and, more generally, in the service literature (Rust & Huang, 2014) that underlines the critical role played by automation in changing how consumers interact with companies (Bitner, Brown, & Meuter, 2000; Verhagen, van Nes, Feldberg, & van Dolen, 2014). Automation has determined a radical shift in customer-assistance methods, whereby automated digital assistants are progressively replacing flesh-and-blood contact personnel (Felfernig et al., 2006), with important implications at the level of individual customer experience (Wirtz et al., 2018). Such a relevant change in customer assistance has been particularly favored by the rise of electronic commerce, since the absence of salespeople that characterizes the online environment might hinder consumer usage of an online store or webpage if consumers are not assisted through automated and interactive tools that subrogate the role of personal assistance (Yoo, Lee, & Park, 2010; Huang & Rust, 2018). In this vein, digital assistants make it possible for consumers to exploit the pros of both the offline and the online channel into a single shopping experience by leveraging both the knowledgeability of assistants characterizing the former (Burke, 2002) and the purchase efficiency typically experienced in the latter (Park & Kim, 2003). However, consumer interactions with digital assistants cannot be restricted to the functional benefits of time saving (Yoon, Hostler, Guo, & Guimaraes, 2013) and efficiency (Satzger, Endres, & Kießling, 2006) in the purchase decision, as previous literature has shown that consumers also derive a set of social benefits from interacting with digital assistants (Wirtz et al., 2018), spanning from the pleasure of direct interaction with the company to feeling important to the firm (Holzwarth, Janiszewski, & Neumann, 2006) and, in general, to the relational elements of the service that stem from human–robot interaction (Stock & Merkle, 2018).

For these reasons, the extant literature shows large consensus on the rapid evolution toward a technology-dominant logic in customer assistance, with digital assistants increasingly becoming the service interface in many industries (Murphy, Hofacker, & Gretzel, 2017; Wirtz et al., 2018) and channels (Larivière et al., 2017). In this vein, previous studies have focused on the quality of the interaction with digital assistants that stimulates positive reactions by consumers when assisted by digital rather than human agents and that minimizes the gap between consumers' expectations and assistants' actual performance (Lee & Choi, 2017). However, when it comes to identifying the specific features underlying consumers' acceptance, results are quite scattered and somewhat contradictory. For instance, the level of customization and the appearance of digital assistants are still controversial issues in the extant literature, as witnessed by the general skepticism and resistance exhibited by customers when interacting with conversational agents (Araujo, 2018).

2.2. Conversational agents

Conversational agents have been defined in the scholarly literature as "computer-generated graphically displayed entities that represent either imaginary characters or real humans controlled by artificial intelligence" (Choi et al., 2001, p. 19). This broad definition includes the many different forms that digital assistants can take, ranging from interactive avatars (Keeling, McGoldrick, & Beatty, 2010) to animated pictures (Zanker, Bricman, & Jessenitschnig, 2011) to human-like animated agents simulating a flesh-and-blood salesperson (Aldiri, Hobbs, & Qahwayi, 2008; Verhagen et al., 2014). Regardless of their level of personification, conversational agents embody the role of customer assistant who actively interacts with online customers, giving them knowledgeable advice and helping them achieve their goals (Zanker et al., 2011) by using their natural language as the communication input and dialoguing in natural language as the output (Griol, Carbó, & Molina, 2013).

Most of the academic research has addressed the features that are more likely to positively affect consumers' evaluation and acceptance of conversational agents as customer assistants: among others, the degree of perceived "intelligence" (Ariely, Lynch, & Aparicio, 2004), the assistant's ability to detect and use consumers' natural language (Mimoun et al., 2012), and the cultural adaptation of conversional style and language (Culley & Madhavan, 2013). Much attention has been devoted to the assistant's physical aspects (Araujo, 2018), including, for instance, level of anthropomorphism (Qiu & Benbasat, 2009), gender (Beldad, Hegner, & Hoppen, 2016); shape, color, sound, or motion (Biocca & Delaney, 1995); and nonverbal behaviors (e.g., nodding or eye gaze, as in Palmer, 1995). With regard to the assistant's appearance, the literature has provided somewhat contradictory findings, since human-like agents were found to be effective in the virtual environment by some studies (e.g., Biocca, 1997; Qiu & Benbasat, 2009), since anthropomorphism better allows denoting some human characteristics that are key to the positive development of interpersonal relationships (Waytz, Cacioppo, & Epley, 2010), while other studies, instead, found that anthropomorphism might be a double-edged sword because it could set too high expectations (Nowak & Rauh, 2008) and because standards for nonverbal communication styles—like anthropomorphic gestures—are subject to huge cultural variations that hinder their universality (Culley & Madhavan, 2013).

2.3. Human reaction to conversational agents

By using AI, firms can provide personalized services based on the individual needs of consumers and their preferences, product wish-lists, and purchase histories. Furthermore, firms can collect vast amounts of data at the individual level by interacting with their customers in multiple channels (Lee & Lee, 2009). Thus, AI could be fed in a way to understand the preference criteria hidden in the customer data and used to satisfy customers' needs and wants by providing highly personalized suggestions. All these processes are usually meant to increase the customer's experience. However, despite widespread euphoria about the value of online personalization, only 10% of consumers actually own an AI device, although 32% would be willing to buy one (Pwc Global Consumer Insights, 2018).

The problem is that consumers often perceive those targeted suggestions as limitations on their personal freedom (Lee & Lee, 2009; Aljukhadar, Trifts, & Senecal, 2017). Thus, they show reactance rather than enthusiasm or gratitude. Reactance is a common psychological response to perceived threats to behavioral freedoms (Brehm, 1966) and typically consists of engaging in an opposite action to deliberately deny the authority who orders it. Individuals react so as to re-establish the threatened freedom, and consumers have been shown to manifest reactance toward both human and artificial agents (Kwon & Chung, 2010; Nass & Moon, 2000). For instance, reactance to IT-based recommendations develops mainly because users perceive the recommendation agents as limiting their freedom of choice rather than as providing advice (Brehm & Brehm, 2013; Aljukhadar & Senecal, 2011).

Accordingly, many studies have investigated possible drivers of reactance to agent recommendations (see Aljukhadar et al., 2017, for a review). In particular, trust has been identified as the key factor that interacts to shape how consumers react to recommendations

(Aljukhadar et al., 2017). Trust reduces consumers' reactance because it increases consumers' willingness to follow the advice of the trusted recommender (Dirks & Ferrin, 2001). Pornpitakpan (2004) suggested that trust and credibility positively influence the likelihood of reacting according to advice. Similarly, McKnight, Choudhury, and Kacmar (2002) found that trust in an online seller leads to higher intention to follow the seller's advice. In summary, trust emerges from the literature as a key feature in lowering reactance to recommendations.

Furthermore, AIs can be designed to look like humans, as in Ikea's digital assistant, or non-humans, as in Aliexpress's digital assistant. Recent literature has advanced anthropomorphism as a potentially relevant dimension of service robots (Wirtz et al., 2018). For instance, trust has been found to be significantly higher for human-like than for non-human-like machines (Waytz, Heafner, & Epley, 2014). Similarly, empathetic intelligence (i.e., the ability to read human emotions) has been suggested as a key element in the acceptance of robots (Huang & Rust, 2018) together with their social-emotional abilities (Wirtz et al., 2018), which in turn consumers positively associate with a human-like appearance (Złotowski, Proudfoot, Yogeeswaran, & Bartneck, 2015). On the same note, anthropomorphic service robots have been found to evoke excitement and happiness in consumers in various different domains, from health (Zhang, Kaber, Zhu, Swangnetr, Mosaly, & Hodge, 2010) to tourism (Murphy, Gretzel, & Hofacker, 2017). Attributing a humanlike mind to a nonhuman agent has been shown to make individuals consider the agent more reliable, capable, and trustworthy as a result of the former's psychological tendency to overuse human social categories (e.g., gender), applying them also to computers, and to engage in overlearned social behaviors, such as politeness toward computers (Nass & Moon, 2000). The attribution of a humanlike mind was found by de Visser et al. (2016) to be much facilitated by a humanlike appearance of robots, and to hold also—and more specifically—for recommendation agents. In summary, behavioral and physiological measures from different studies confirm that individuals feel greater trust for computer agents that display more anthropomorphic features (de Visser et al., 2017; Seeger & Heinzl, 2018).

Combining the considerations about trust in anthropomorphic agents with those about the impact of trust on reactance, one could argue that because trust reduces reactance, and because trust tends to be higher in anthropomorphic agents, these should lead to lower reactance.

More formally, we advance the following:

H1a: An anthropomorphic digital assistant leads to lower reactance than a non-anthropomorphic one.

Furthermore, previous studies have addressed digital agents as a useful tool for simplifying the processing of information provided on webpages (Sivaramakrishnan, Wan, & Tang, 2007) by prescreening alternatives to provide a more compact consideration set to choose from (Alba et al., 1997), thus simplifying the decision-making process (Payne, Bettman, & Johnson, 1993). Accordingly, the role of digital assistants is to interpret and elicit consumer preferences by using previous information about each consumer as a basis in which to formulate a customized suggestion (McGinty & Smyth, 2006). On one hand, previous studies have shown that such recommendations by digital assistants are among the most powerful sources of choice certainty (Gretzel & Fesenmaier, 2006). On the other hand, the literature has shown that suggestion customization might paradoxically come at the expense of consumers' perceptions of their freedom of choice (Aguirre et al., 2015), where such a "personalization without interrogation" (Murray & Häubl, 2009) is perceived as a limitation on one's freedom. This is to say, unsolicited advice from digital assistants might harm consumers and their reactions to the retailer (Feng & Magen, 2016) because of the potential reactance from such recommendations (Fitzsimons &

Lehmann, 2004; Lee & Lee, 2009). In turn, previous research has documented that one of the relevant consequences of reactance is that consumers ignore recommendations (Edwards, Li, & Lee, 2002); for instance, pop-up advertisements producing reactance are discarded by consumers, and customized e-mails yield results opposite to the advice they contain (White, Zahay, Thorbjørnsen, & Shavitt, 2008).

Accordingly, we hypothesize as follows:

H1b: User-initiated digital assistants lead to lower reactance than computer-initiated digital assistants.

In H1a we posited that non-human-like digital assistants lead to higher reactance due to the lower social-emotional abilities attributed to non-human-like agents. In H1b we posit that system-initiated digital assistants lead to higher reactance because the unsolicited advice could be perceived as a threat to consumers' freedom of choice.

Previous studies have shown that reactance can stem from different sources simultaneously, together increasing reactance and the number and proportion of freedoms threatened (Shen, 2015). Accordingly, we posit that the two potential sources for reactance identified by H1a and H1b could add up. Specifically,

H1c: Reactance will be lower (higher) for (non-)anthropomorphic digital assistants that are initiated by consumers (automatically).

Note that establishing a sense of control and personal freedom by manifesting reactance does not always lead individuals to the best outcome. Some advice could have actually been good and meant not to threaten personal freedom but rather to help consumers find the best solution more easily. In other words, the activation of reactance "can automatically elicit oppositional goal pursuits, even when pursuit of an oppositional goal results in a personally suboptimal outcome" (Chartrand, Dalton, & Fitzsimons, 2007, p. 719). This pattern has been widely documented; for instance, the perception of a health advertisement as highly intrusive has been shown to disrupt perceived freedom (Edwards et al., 2002) and to materialize into *more* rather than less smoking (Quick, Scott, & Ledbetter, 2011). Similarly, labels warning of violent content have been found to potentially lead to more interest in viewing violent entertainment (Bushman & Stack, 1996), and the choice of unhealthy food products is increased after reading recommendations for healthier brands (Fitzsimons & Lehmann, 2004).

Additionally, as a result of psychological reactance, consumers will also experience increased difficulty in the decision-making process because "they must resolve the conflict between their attitudes and the recommendation" (Fitzsimons & Lehmann, 2004, p. 84).

Such difficulty reconciling one's attitudes with others' advice/recommendation might reduce individuals' perceptions about the fluency of the choice task (Novemsky, Dhar, Schwarz, & Simonson, 2007) because elements that individuals might use to justify their choices are conflicting (Shafir, Simonson, & Tversky 1993).

In this regard, previous research witnessed a causal relationship between conflicting information and the decision-making process (Carmon, Wertenbroch, & Zeelenberg, 2003), which can be induced by the recommendations that consumers are exposed to during the process (Goodman, Broniarczyk, Griffin, & McAlister, 2013).

Accordingly, we hypothesize as follows:

H2: Higher levels of reactance lead to higher levels of choice difficulty.

Previous studies have shown that choices made under conditions of higher difficulty require greater cognitive effort (Garbarino & Edell, 1997). In turn, the greater the effort made to make a decision, the greater the sunk cost of revising that decision and therefore the greater the pressure on the decision-maker (Moon, 2001). Arkes and Blumer (1985) showed that sunk costs increase one's estimated probability that an endeavor will succeed, leading individuals to be more committed. Similarly, Arkes and Hutzel (2000) showed that sunk costs lead to a higher tendency to be involved with the consequences of the choice made.

The combined evidence from these previous studies suggests that when a choice is reached after greater fatigue, the sunk costs of such a choice activate psychological mechanisms akin to cognitive dissonance (Sweeney, Hausknecht, & Soutar, 2000), reinforcing choice certainty (Harmon-Jones, 2002). Furthermore, the more difficult a decision is, the longer the time needed to make it (Haynes, 2009). Recent studies have established a positive link between the time needed to make a decision and the certainty of that decision (Kiani, Corthell, & Shadlen, 2014). That is to say, the extent to which individuals perceive that they have undertaken a difficult decision-making process affects their subjective evaluation of the quality of their choice because they did not stop at a satisficing option (Mills, Meltzer, & Clark, 1977) but rather screened the available options more efficiently (Häubl & Trifts, 2000).

Accordingly, we posit as follows:

H3: Higher levels of choice difficulty lead to higher levels of choice confidence.

In turn, it is widely accepted in the literature that confidence affects the extent to which individuals evaluate their performance, or their judgment of their own efficacy capability in a specific setting (Ellen, Bearden, & Sharma, 1991). This finding holds in several different contexts, such as self-confidence in one's performance (Woodman & Hardy, 2003), employee confidence in job performance (De Jong, De Ruyter, & Wetzels, 2006), initial confidence in task initiation and performance (Lefcourt, Hogg, Struthers, & Holmes, 1975), competitive confidence in sports performance (Levy, Nicholls, & Polman, 2011), team confidence in team performance (Fransen, Haslam, Steffens, Vanbeselaere, De Cuyper, & Boen, 2015), and computer confidence in e-learning performance (Su & Klein, 2006). This relationship has been found also for choice confidence in both traditional (Perfect, 2004; Andrews, 2013) and computer-mediated environments (Häubl & Trifts, 2000). Specifically, with regard to the usage of technologies, research has indicated that the way individuals evaluate technological assistance to be useful and consistent with their task affects their perceptions of their individual performance (Dishaw & Strong, 1999).

Accordingly, we hypothesize as follows:

H4: Higher levels of choice confidence lead to higher levels of perceived individual performance in the purchase decision.

The literature has widely documented the role of perceived performance in satisfaction evaluation, building on the expectancy-disconfirmation theory that posits that individuals develop their satisfaction judgments as a comparative evaluation between their expectancies and their performance (Oliver, 2014). Previous studies have investigated individual levels of decision satisfaction (Valenzuela, Dhar, & Zettelmeyer, 2009) that arise as a function of the extent to which the choice outcome exceeds consumers' expectations (Wang & Shukla, 2013). Similarly, previous studies in offline settings have shown that consumers' perceptions of their choice-task performance significantly and positively affect their satisfaction (Iyengar & Lepper, 2000). Accordingly, we posit the existence of a similar relationship in a computer-mediated environment. Specifically,

H5: Higher levels of perceived individual performance in the purchase decision lead to higher levels of choice satisfaction.

Two final points need to be made about choice satisfaction, one regarding anthropomorphism and one regarding user initiation. First, as mentioned, reactance rarely leads to the best outcome when individuals purposely reject helpful advice (Chartrand et al., 2007). Consequently, satisfaction is lower when reactance is present (Hong & Giannakopoulos, 1994; Lamberton, 2013). Given that we posit that reactance would be higher for non-human-like assistants, it follows that satisfaction should be lower when consumers are exposed to them rather than to human-like assistants.

Furthermore, the literature has suggested that anthropomorphism could be associated with satisfaction (Murano & Holt, 2011; Johnson & Acquavella, 2012) because anthropomorphized objects facilitate interactions in nonmaterial contexts (Brown, 2010). Along the same lines, the specific psychological processes underlying anthropomorphism (Epley, Waytz, & Cacioppo, 2007) have been suggested to make virtual-agent personification a predictor of user satisfaction (Purington, Taft, Sannon, Bazarova, & Taylor, 2017) and of satisfaction-related constructs such as social response, compliance, and performance in decision-making tasks (Bass, Fink, Price, Sturre, Hentschel, & Pak, 2011), as anthropomorphism enhances comfort of use and decreases uncertainty (Freling & Forbes, 2005).

Finally, anthropomorphism is a natural human tendency (Guthrie, 1997; Epley et al., 2007) and “a phenomenon that pervades the everyday thoughts and actions of most individuals and influences human perceptions and responses throughout life” (Lombart & Louis, 2012, p. 645). Thus, digital assistants whose appearance facilitates the natural human tendency to anthropomorphize should be positively related to higher satisfaction.

Although they are epistemologically different, these considerations provide theoretical support for the following hypothesis:

H6a: An anthropomorphic digital assistant leads to higher levels of choice satisfaction than does a non-anthropomorphic one.

Second, regarding user initiation, research has shown that individuals tend to derive different levels of satisfaction depending on whether they attribute the responsibility of the outcome to themselves or to the company (Oliver & DeSarbo, 1988; Tsiros, Mittal, & Ross, 2004). Accordingly, consumers might attribute less responsibility to themselves if the digital assistant has not been activated purposely by themselves (i.e., but automatically by the system). Thus, we expect consumers to exhibit different levels of satisfaction depending on whether they interacted with a digital assistant activated by themselves or activated externally. Specifically, we hypothesize as follows:

H6b: A user-initiated digital assistant leads to higher levels of choice satisfaction than does a computer-initiated one.

In summary, we hypothesize a sequential mediation model whereby reactance, choice difficulty, choice certainty, and perceived performance mediate the relationship between the type and the activation of digital assistants and consumers' satisfaction with their choice (Fig. 1).

FIGURE 1 ABOUT HERE

3. Method

3.1. Design

Two experimental studies were implemented to test the theoretical model presented in Fig. 1. To this end, the studies adopted a 2 (assistant type: anthropomorphic vs. non-anthropomorphic) × 2 (assistant initiation: user- vs. system-initiated) between-subjects experimental design. First, four mock-up webpages mimicking existing comparators for mobile tariff plans (Study 1) and car rental (Study 2) were generated and pretested for realism, which served as experimental stimuli for the experimental conditions. In both Studies, the 15 options presented were kept constant across the four experimental conditions and featured real brands and real tariff plans (Study 1) / car rental options (Study 2) available on the market at the time of data collection (July 2018 and August 2019 respectively). The tariff plans were compared for Service Provider Brand Name, Voice Minutes Included in the plan, Text Messages Included in the plan, Gigabytes of Internet Connection Included in the plan, and monthly Price. The car rental options were compared for Service Provider Brand Name, Damage Excess, Deposit at Pick-up, Car Segment, and Daily Price. The image of the mock-up page was then uploaded on Qualtrics to serve as the starting point for the questionnaire immediately after an introductory section. In Study 1, as a cover story, participants were asked to imagine that they had to move to Italy for a temporary but long-term stay and thus needed to choose a tariff plan from a local provider for their mobile phone during their stay. Similarly, in Study 2, participants were asked to imagine that they were about to visit Italy for a holiday and thereby needed to rent a car. Accordingly, Italian participants were excluded from participating in the study to prevent their simply replicating the choice of their own tariff plan / excluding car rental since they might use their own car.

Participants could either immediately select a choice option or ask for assistance from the digital assistant. Hot-spot areas (invisible to respondents) were set up on Qualtrics to register the selection clicked by each participant.

Participants in the system-initiated condition saw the chat box of either the anthropomorphic or the non-anthropomorphic digital assistant already opened with the message “How can I help you?” written in the chat box. In the user-initiated condition, the digital assistant appeared silent and minimized at the right bottom of the page, and participants choose whether to activate the digital assistant by clicking on it or not. Until the digital assistant was clicked on, it remained minimized, showing either the anthropomorphic or non-anthropomorphic avatar—depending on the experimental condition—and the message “Click here if you need help.” Participants were therefore exposed to the opened chat box, as in the system-initiated condition, only if they clicked on it.

Regardless of the assistant initiation condition, participants could interrogate the assistant to filter options that matched their search criteria in terms of the attributes at the basis of the comparison. After digital-assistant interrogation, the mock-up webpage changed by filtering out all options that did not match the criteria that participants indicated to the assistant. At this stage, participants were asked to complete their choice by selecting one of the options in the reduced-choice set. Examples of the stimuli are in Appendix Fig. A1 and A2.

After completing the choice task, participants were redirected to the next section of the questionnaire, as detailed in the following paragraph.

3.2. Sample and measurements

For each study, data were collected through an online questionnaire developed in Qualtrics and administered each time to 200 consumers (S1: Mean age = 33.27, Median age = 29; 48.4%

females; S2: Mean age = 31.31, Median age = 29; 47.5% females) recruited from a panel held by a market research company, ensuring the representativeness of the target population of customers of the chosen service category. Respondents were randomly exposed to one of four experimental conditions according to a 2 (anthropomorphic vs. non-anthropomorphic digital assistant) × 2 (user- vs. computer-initiated digital assistant) between-subjects design and asked to fill a questionnaire. The present study adapted measures for psychological reactance (i.e., perceived threat to freedom) and perceived performance from Drennan and McColl-Kennedy (2003); choice difficulty from Dhar and Nowlis (2004); choice confidence from Laroche, Kim, and Zhou (1996); and choice satisfaction from Fitzsimons (2000). Respondents in Study 2 were also asked to rate their user experience (Finstad 2010), and their familiarity with the product category (as in Kent and Allen 1994). All items were measured using 7-point scales. The items are listed in Appendix Table A.1.

Next, respondents answered the usual demographic questions (age, gender, occupation, education), and were thanked and debriefed; all participants passed an attention check.

4. Results

4.1. Scales and measurements

We followed Anderson and Gerbing's (1988) procedure to ensure the adequacy of our measurements. Thus, we first ran a confirmatory factor analysis, whose results provide support for the convergent validity of the measures. All factor loadings exceed the recommended .60 threshold (Bagozzi & Yi, 1988), the composite reliability (CR) measures exceed the recommended .70 thresholds, and the average variance extracted (AVE) exceeded the recommended .50 threshold (Fornell & Larcker, 1981). Specifically, the minimum CR is .79, and the minimum AVE is .66. Results are provided in Appendix Table A.1.

Next, we ran a test of discriminant validity based on the comparison of the AVE estimate for each construct with the squared correlation between any two constructs (Fornell & Larcker, 1981). Discriminant validity is confirmed as the lowest AVE (.52) exceeds the highest squared correlation between any two variables (.42). The measurement model therefore meets all relevant psychometric properties. Details are provided in Appendix Table A.2.

4.2. Sequential mediation models

Three sequential mediation analyses with four mediators were run for each study using the PROCESS 3.0 macro for SPSS 25 (Model 6; see Hayes, 2018) to assess the causal sequence from digital-assistant type (anthropomorphic vs. non-anthropomorphic) and from digital-assistance initiation (human- vs. computer-initiated)—respectively—to choice satisfaction, as advanced in the theoretical model in Fig. 1. Choice satisfaction was the dependent variable; reactance, choice difficulty, choice certainty, and perceived performance were sequential mediators of the relationship between the dependent and the independent variables.

Study 2 also allowed to enter respondent's age and familiarity with the product category as possible covariates to control for in the model.

4.2.1. Study 1: mobile phone tariffs plans

When considering the type of digital assistant, the overall pathway from assistant type to purchase intention through reactance, choice difficulty, choice certainty, and perceived performance was significant, as the 95% confidence interval (CI) did not include zero (indirect effect = .015, 95%CI: −.040 to −.001). Specifically, the non-anthropomorphic digital assistant led to higher reactance ($B = .605$; $p = .031$), providing support for H1a. As advanced in H2, reactance significantly affected consumers' perceptions of choice difficulty ($B = .677$; $p < .001$).

In line with H3, consumer perceptions of choice difficulty positively related to choice certainty ($B = .271$; $p = .007$). In turn, as advanced in H4, choice certainty significantly and positively affected perceived performance ($B = .236$; $p = .007$), which in turn positively influenced choice satisfaction ($B = .570$; $p < .001$), as hypothesized in H5.

When considering instead the initiation of the digital assistant, we found no relationship with reactance ($B = .074$; $p = .792$), thus rejecting H1b and providing no support for the sequential mediation model when starting from digital-assistant initiation, with the indirect path being no longer significant, as the 95% CI included zero (indirect effect = −.002, 95%CI: −.018 to .009).

A further check ensured that neither assistant type nor initiation had a direct impact on choice difficulty (Effects: type = −.023; $p = .911$; initiate = −.157; $p = .445$), choice certainty (Effects: type = .313; $p = .190$; initiate = −.281; $p = .234$), or perceived performance (Effects: type = .333; $p = .10$; initiate = −.150; $p = .420$). Furthermore, neither the direct path from assistant type to choice satisfaction (Effect = .103; $p = .412$) nor the direct path from assistant initiation to choice satisfaction (Effect = −.065; $p = .597$) was found to be significant, thus rejecting H6a and H6b respectively. This evidence further suggests that reactance, choice difficulty, choice certainty, and perceived performance fully mediate the relationship between digital-assistant type and consumers' choice satisfaction.

Finally, to test for H1c, the interaction term Digital assistant type × Initiation was computed and used as the independent variable in the sequential mediation chain. Overall, results confirm each step of the sequential chain and furthermore show that the interaction term significantly affects reactance (Effect = .632; $p = .047$). The results show that initiation per se does not activate the chain of effects but that it significantly interacts with anthropomorphism, so that individuals exhibit lower reactance when confronted with a human-like digital assistant that they themselves have activated. Instead, reactance is highest for non-human-like digital assistants that are computer-initiated. This evidence provides support for H1c.

The results of the PROCESS 3.0 macro are summarized in Table 1 and graphically reported in Fig. 2.

TABLE 1 ABOUT HERE

4.2.2. Study 1: discussion of the findings

Results from Study 1 support a full mediation from digital assistant type and activation to choice satisfaction. Specifically, results from Study 1 indicate that non-anthropomorphic digital assistants induce more reactance than anthropomorphic digital assistants. With respect to the assistant activation (if spontaneously by the customer or initiated automatically), no main effect on reactance is identified. However, preliminary results indicate a significant interaction between assistant initiation and anthropomorphism, which emphasizes the extent to which the highest levels of reactance are triggered by a non human-like digital assistant that is automatically activated.

Consumer reactance is proven to be a key construct in the chain of effects following consumers' exposure to a digital assistant because the higher consumer reactance, the higher the choice difficulty experienced by customers. Choice difficulty might sound a disappointing result for a retailer. Conversely, results from Study 1 show that choice difficulty is not necessarily detrimental for customers, since it drives perceptions of higher certainty about the quality of the final choice. This, in turn, leads customers to perceive a higher choice performance, which ultimately increases choice satisfaction.

Overall, results from Study 1 support the pattern of causal effects hypothesized in the theoretical model, but should be read in the light of the intrinsic limitations of this study. Indeed, Study 1 is conducted in a single experimental setting (mobile tariff plans) which might undermine its generalizability due to the relatively low involvement of the decision-making process and the intangibility of the offering.

Furthermore, the study purposely compared four different combinations of assistant anthropomorphism and activation; however, it does not address how consumers would have reacted, if they had not been exposed to any type of digital assistant. In addition, the outcomes of consumer perceptions after interacting with a digital assistant might go beyond transaction-specific evaluations such as choice satisfaction, and extend to more general evaluations about the webpage, such as user experience. For this reason, the subsequent study 2 has the purpose of addressing these limitations emerging from Study 1, by considering the purchase of a different (and physical) product, including an experimental condition without digital assistance, and addressing perceived user experience.

4.2.3. Study 2: car rental plans

Study 2 aims to validate the results of Study 1 and to advance the findings of Study 1 along several directions: first, it examines if the same pattern of results still holds in a different category (car rentals versus mobile tariff plans). Second, it adds a hanging control group to the experimental design in order to provide a baseline for the effects. Third, it explores the same chain of effects from assistant type and initiation on an additional dependent measure, that is to say user experience. Finally, it controls for the effect of possible covariates that might potentially influence consumer reactions to digital assistants, such as the respondent's age and experience with the product category.

First, a Multivariate Analysis of Variance (MANOVA) yielded a significant main effect of the digital assistant (Wilks λ = .74, F = 2.47, df = 24; 654, p < .001, η^2 = .07) and gender (Wilks

$\lambda = .87$, $F = 4.82$, $df = 6; 187$, $p < .001$, $\eta^2 = .13$) on the dependent measures. Univariate tests following the significant MANOVA show that gender, as a covariate, affects reactance ($F = 7.13$, $df = 1; 192$, $p = .008$, $\eta^2 = .04$) and decision satisfaction ($F = 4.38$, $df = 1; 192$, $p = .038$, $\eta^2 = .02$). Specifically, women display higher reactance ($M_F = 3.83$ vs. $M_M = 3.31$), and lower decision satisfaction ($M_F = 4.70$ vs. $M_M = 5.02$). They also show a main effect of the digital assistant on reactance ($F = 7.62$, $df = 4; 192$, $p < .001$, $\eta^2 = .14$). Specifically, when the digital assistant is anthropomorphic and user-initiated ($M_{ANTR\_UI} = 2.94$), reactance is lowest and even lower than in the control group where respondents saw no digital assistant ($M_{CG} = 3.74$).

Then, running the PROCESS macro on SPSS as in Study 1 to test the conceptual model, again shows a significant overall indirect effect from assistant type and initiation on both decision satisfaction (indirect effect = .02, 95%CI: .001 to .055) and user experience (indirect effect = .03, 95%CI: .001 to .083), once again providing evidence for the robustness of the conceptual model. As in Study 1, the non-anthropomorphic digital assistant led to higher reactance (B = -.505; p = .039). Similarly to Study 1, no main effect of assistant initiation on reactance emerged (B = .406; p = .100), but initiation significantly interacts with assistant type in affecting consumer reactance (B = -.689; p = .044), suggesting that men tend to display lower reactance that women. In line with the MANOVA, reactance was affected also by gender (B = -.340; p = .050). In turn, reactance affected consumers' perceptions of choice difficulty (B = .296; p = .001), which was found to be affected also by consumers' familiarity with the product category (B = .207; p = .013). Choice difficulty had an impact on choice certainty (B = .603; p < .001) that contributed to perceived performance (B = .557; p < .001). Finally, confirming the path of sequential mediation that emerged from Study 1, perceived performance influenced choice satisfaction (B = .403; p < .001). In line with the MANOVA, decision satisfaction was affected also by gender and was higher for men than for women (B = .286; p = .032). Furthermore, Study 2 addresses also user experience as dependent variable, showing that it is significantly affected by perceived performance (B = .608; p < .001).

As for Study1, also in Study 2 neither assistant type nor initiation type had a direct impact on choice difficulty (Effects: type = .045; p = .868; initiate = -.112; p = .676), choice certainty (Effects: type = -.106; p = .690; initiate = -.205; p = .434), or perceived performance (Effects: type = 237; p = .372; initiate = .449; p = .090), thus fully adhering to the evidence emerging from Study 1. Similarly, the direct path from assistant type to choice satisfaction (Effect = .291; p = .114) was not found to be significant, once more corroborating that reactance, choice difficulty, choice certainty, and perceived performance fully mediate the relationship between digital-assistant type and consumers' choice satisfaction. Partial mediation emerged for assistant initiation which directly affects choice satisfaction (Effect = .490; p = .008).

The results of the PROCESS 3.0 macro are summarized in Table 1 and graphically reported in Figure 2.

4.2.4. Study 2: discussion of the findings

Results from Study 2 align with those from Study 1 in showing that initiation *per se* does not activate the chain of effects, but that it significantly interacts with anthropomorphism, so that reactance is lower for user-initiated anthropomorphic assistants, and higher for system- initiated non-anthropomorphic assistants. These results further validate our theoretical model.

In addition, results from Study 2 corroborate the robustness of the theoretical model, by demonstrating that the same findings emerge when controlling for customers' age, gender, and familiarity with the choice context. Finally, Study 2 suggests that the presence, the appearance and the locus of activation of digital assistants exert an effect on consumer perceptions that goes beyond the mere transactional considerations about choice satisfaction, and extends to how users evaluate their overall experience with the webpage.

5. Discussion and conclusion

As a consequence of the increasing automation in services, the attention of researchers and practitioners is moving toward the development of new digital systems to improve online consumers' assistance (Felfernig et al., 2006; Yoo et al., 2010). This process might generate different consumer reactions (Holzwarth et al., 2006; Kwon & Chung, 2010; Nass & Moon, 2000). Accordingly, the present study investigated a particular form of automated digital assistance for online consumers based on an AI and ML application, the conversational agent. In particular, the results of our study respond to the need for further evidence on how AI might affect different industries (Huang & Rust, 2018). To do so, the present research used choice satisfaction and user experience as dependent variables and addressed the role of the digital assistant's appearance (anthropomorphic vs. non-anthropomorphic) and initiation (user- vs. system-initiated) in determining consumers' reactance, which, in turn, triggers a sequence of consumers' evaluations of the decision-making process. Specifically, this research found a significant mediation chain from digital-assistant appearance to consumers' choice satisfaction and user experience through reactance, choice difficulty, choice certainty, and perceived performance in the choice task, moderated by the assistant's initiation. In particular, results show that non-anthropomorphic digital assistants increase reactance, which enhances choice difficulty, leading to more choice certainty that improves perceived performance, which ultimately positively affects satisfaction (H1a, H1c, H2, H3, H4, H5, and H6a are supported). Conversely, results from both studies show that whether the digital assistant was initiated by the consumer or not has no effect per se. However, initiation interacts with anthropomorphism, so that reactance is minimized when a human-like digital assistant is activated by the consumer and is maximized when a non-human-like assistant activates automatically (H1b and H6b are not supported). Therefore, our findings also add new knowledge about how automated services change the way of interacting with consumers (Bitner et al., 2000; Verhagen et al., 2014) by identifying the drivers of consumers' satisfaction with a digitally assisted choice.

Furthermore, with regards to the debate on service dominant logic, our results contribute answering to recent calls to better understand the determinants of successful human–machine integrations (Ng & Vargo, 2018; Vargo & Lusch, 2017). Specifically, our finding show the extent to which AI- and ML-based technologies promote the consumer value creation. We find that these new systems adequately engage consumers, while the service exchange between consumer and retailer (represented by the technology) occurs to create value. Drawing upon Vargo and Lusch's (2017) suggestion to align cognitive computing with service-dominant logic, our findings further show the extent to which customer assistance service would represent a powerful resource to provide and obtain (customer) service. Accordingly, AI- and ML-based technologies as chatbots can proactively predict and assist users (consumers) behaviors, needs and requests, and might represent the evolution of the service dominant logic ecosystems into the marketing domain.

Overall, the evidence from the present research contributes to previous literature and to the service dominant logic debate by relating consumers' acceptance of AI to the characteristics of the digital assistant rather than focusing on the mere presence of digital assistance (Larivière et al., 2017; Lee & Choi, 2017). Furthermore, the present research includes considerations from consumer psychology in addressing how consumers might react to the interaction with their digital counterpart by specifically accounting for psychological reactance and self-assessment.

From a managerial perspective, our results clearly indicate that an automatically activated non-anthropomorphic digital assistant leads to higher levels of satisfaction and user experience than a human-like, consumer-activated digital assistant. Note that such improvement in choice satisfaction and user experience comes from a potentially negative starting condition, as it is higher reactance that activates the chain of effects leading to satisfaction. Thus, an accurate balance is needed between the potential final benefits in terms of satisfaction and experience with automatically activated non-anthropomorphic digital assistants and their potential initial disadvantages in terms of threats to consumers' perceived freedom of choice and choice difficulty. Therefore, marketing managers are encouraged to jointly evaluate the level of anthropomorphism and the activation of the digital assistant in order to identify the optimal balance between initial reactance and final satisfaction. In this way, companies would be able to provide better-customized recommendations that consumers will be more willing to accept while delivering a more satisfactory experience.

6. Limitation and future research

The results of the present research show some limitations that suggest directions for future study. For instance, the extant literature has highlighted a negative direct relationship between reactance and satisfaction (Fitzsimons & Lehmann, 2004), such that lower levels of reactance increase satisfaction. The present research instead shows the existence of an indirect positive effect, mediated by choice difficulty, confidence, and perceived performance. Future studies could manipulate the size of the assortment from which consumers must choose in order to assess whether the negative relationship between reactance and satisfaction could be ascribed to choice overload, a common feature in online settings (Lee & Lee, 2004).

Furthermore, future studies could address consumers' interaction with conversational agents when browsing with a learning goal or choosing in a familiar domain. Also, our results do not focus on the natural language and realism of interaction as possible mediators of consumers' reactance; future studies might explicitly consider these features in understanding customer–AI interactions. Similarly, our study does not take into account the extent to which the collaboration between consumers and digital assistant/AI systems might improve the quality of recommendations. Further studies might investigate this gap, drawing from recent studies on learning from digital interactions (Rezai et al., 2019) and transposing them specifically in the context of AI in order to investigate how human-AI collaboration (Hill, Ford, and Farreras, 2015) could improve recommendations.

Moreover, our research does not explicitly analyze the effect of users' interaction with the chatbot on the experience, as proposed by past studies (Van de Broeck, Zarouali and Poles, 2019; Hill, Ford and Farreras, 2015). Thus, our results could be the starting point to further investigate the overall consumers' experience in the retail settings enriched with the above-mentioned conversational technologies.

Finally, the present study manipulated anthropomorphism dichotomously. Future studies might design stimuli with different degrees of human resemblance such as, for instance, in Yee, Bailenson, and Rickertsen (2007), to understand whether consumers' reactions to anthropomorphism change along a continuum. In this vein, future studies could also compare consumers reactions in the new digital environment with the traditional interactions with human-assistants (Hill, Ford and Ferreras, 2015), thus answering recent calls by Vannucci and Pantano (2019).

References

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing, 91*(1), 34–49.

Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive home shopping: consumer, retailer, and manufacturer incentives to participate in electronic marketplaces. *The Journal of Marketing, 61*(3), 38–53.

Aldiri, K, Hobbs, D., & Qahwayi, R. (2008). The human face of e-business: engendering consumer initial trust through the use of images of sales personnel on e-commerce web sites. *Journal of E-Business Research*, 4, 58-78.

Aljukhadar, M., & Senecal, S. (2011). Usage and success factors of commercial recommendation agents: A consumer qualitative study of MyProductAdvisor. com. *Journal of Research in Interactive Marketing, 5*(2/3), 130–152.

Aljukhadar, M., Trifts, V., & Senecal, S. (2017). Consumer self-construal and trust as determinants of the reactance to a recommender advice. *Psychology & Marketing, 34*(7), 708–719.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., . . . & Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer Needs and Solutions, 5*(1–2), 28–37.

Andrews, D. (2013). The interplay of information diagnosticity and need for cognitive closure in determining choice confidence. *Psychology & Marketing, 30*(9), 749–764.

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.

Ariely, D., Lynch, J. G., Jr., & Aparicio, M., IV. (2004). Learning by collaborative and individual-based recommendation agents. *Journal of Consumer Psychology, 14*(1–2), 81–95.

Arkes, H. R., & Blumer, C. (1985). The psychology of sunk cost. *Organizational Behavior and Human Decision Processes, 35*(1), 124–140.

Arkes, H. R., & Hutzel, L. (2000). The role of probability of success estimates in the sunk cost effect. *Journal of Behavioral Decision Making, 13*(3), 295–306.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74–94.

Baier, D., & Stüber, E. (2010). Acceptance of recommendations to buy in online retailing. *Journal of Retailing and Consumer Services, 17*(3), 173–180.

Baloian, N., Galdames, P., Collazos, C.A., & Guerrero, L.A. (2004). A model for a collaborative recommender system for multimedia learning material. In Groupware: Design, Implementation, and Use, *Lecture Note in Computer Science*, 3198, 281-288.

Bass, B., Fink, N., Price, M., Sturre, L., Hentschel, E., & Pak, R. (2011, September). How does anthropomorphism affect user's trust, compliance, and performance on a decision making automation task? In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 55, No. 1, pp. 1952–1956). Sage CA: Los Angeles, CA: SAGE Publications.

Beldad, A., Hegner, S., & Hoppen, J. (2016). The effect of virtual sales agent (VSA) gender–product gender congruence on product advice credibility, trust in VSA and online vendor, and purchase intention. *Computers in Human Behavior*, *60,* 62–72.

Bertacchini, F., Bilotta, E., & Pantano, P. (2017). Shopping with a robotic companion. *Computers in Human Behavior, 77*, 382–395.

Biocca, F. (1997). The cyborg's dilemma: Progressive embodiment in virtual environments. *Journal of Computer-Mediated Communication, 3*(2), JCMC324.

Biocca, F., & Delaney, B. (1995). Immersive virtual reality technology. *Communication in the Age of Virtual Reality, 15*, 32.

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. *Journal of the Academy of Marketing Science, 28*(1), 138–149.

Brehm, J. W. (1966). *A theory of psychological reactance.* Oxford, England: Academic Press.

Brehm, S. S., & Brehm, J. W. (2013). *Psychological reactance: A theory of freedom and control.* Academic Press.

Brown, S. (2010). Where the wild brands are: Some thoughts on anthropomorphic marketing. *The Marketing Review, 10*(3), 209–224.

Burke, R. R. (2002). Technology and the customer interface: What consumers want in the physical and virtual store. *Journal of the Academy of Marketing Science, 30*(4), 411–432.

Bushman, B. J., & Stack, A. D. (1996). Forbidden fruit versus tainted fruit: Effects of warning labels on attraction to television violence. *Journal of Experimental Psychology: Applied, 2,* 207–226.

Carmon, Z., Wertenbroch, K., & Zeelenberg, M. (2003). Option attachment: When deliberating makes choosing feel like losing. *Journal of Consumer Research, 30*(1), 15–29.

Chartrand, T. L., Dalton, A. N., & Fitzsimons, G. J. (2007). Nonconscious relationship reactance: When significant others prime opposing goals. *Journal of Experimental Social Psychology, 43*(5), 719–726. .

Choi, Y. K., Miracle, G. E., & Biocca, F. (2001). The effects of anthropomorphic agents on advertising effectiveness and the mediating role of presence. *Journal of Interactive Advertising*, *2*(1), 19–32.

Culley, K. E., & Madhavan, P. (2013). A note of caution regarding anthropomorphism in HCI agents. *Computers in Human Behavior*, *29*(3), 577–579.

De Jong, A., De Ruyter, K., & Wetzels, M. (2006). Linking employee confidence to performance: A study of self-managing service teams. *Journal of the Academy of Marketing Science*, *34*(4), 576–587.

de Visser, E. J., Monfort, S. S., Goodyear, K., Lu, L., O'Hara, M., Lee, M. R., . . . & Krueger, F. (2017). A little anthropomorphism goes a long way: Effects of oxytocin on trust, compliance, and team performance with automated agents. *Human Factors*, *59*(1), 116–133.

de Visser, E. J., Monfort, S. S., McKendrick, R., Smith, M. A., McKnight, P. E., Krueger, F., & Parasuraman, R. (2016). Almost human: Anthropomorphism increases trust resilience in cognitive agents. *Journal of Experimental Psychology: Applied*, *22*(3), 331.

Dahl, A.J., Milne, G.R., & Peltier, J.W. (2019). Digital health information seeking in an omni-channel environment: a shared decision-making and service-dominant logic perspective. *Journal of Business Research, forthcoming*, DOI: 10.1016/j.jbusres.2019.02.025.

Dhar, R., & Nowlis, S. M. (2004). To buy or not to buy: Response mode effects on consumer choice. *Journal of Marketing Research*, *41*(4), 423–432.

Dirks, K. T., & Ferrin, D. L. (2001). The role of trust in organizational settings. *Organization Science*, *12*(4), 450–467.

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management*, *36*(1), 9–21.

Drennan, J., & McColl-Kennedy, J. R. (2003). The relationship between Internet use and perceived performance in retail and professional service firms. *Journal of Services Marketing, 17*(3), 295–311.

Edvardsson, B., Ng, G., Min, C.Z., Firth, R., & Yi, D. (2011). Does service-dominant design result in a better service system?. *Journal of Service Management, 22*(4), 540-556.

Edwards, S. M., Li, H., & Lee, J. H. (2002). Forced exposure and psychological reactance: Antecedents and consequences of the perceived intrusiveness of pop-up ads. *Journal of Advertising, 31*(3), 83–95.

Ellen, P. S., Bearden, W. O., & Sharma, S. (1991). Resistance to technological innovations: An examination of the role of self-efficacy and performance satisfaction. *Journal of the Academy of Marketing Science, 19*(4), 297–307.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review, 114*(4), 864.

Felfernig, A., Friedrich, G., Jannach, D., & Zanker, M. (2006). An integrated environment for the development of knowledge-based recommender applications. *International Journal of Electronic Commerce, 11*(2), 11–34.

Feng, B., & Magen, E. (2016). Relationship closeness predicts unsolicited advice giving in supportive interactions. *Journal of Social and Personal Relationships, 33*(6), 751–767.

Finstad, K. (2010). The usability metric for user experience. *Interacting with Computers, 22*(5), 323-327.

Fitzsimons, G. J. (2000). Consumer response to stockouts. *Journal of Consumer Research, 27*(2), 249–266.

Fitzsimons, G. J., & Lehmann, D. R. (2004). Reactance to recommendations: When unsolicited advice yields contrary responses. *Marketing Science, 23*(1), 82–94.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research, 18*(3), 382–388.

Fransen, K., Haslam, S. A., Steffens, N. K., Vanbeselaere, N., De Cuyper, B., & Boen, F. (2015). Believing in "us": Exploring leaders' capacity to enhance team confidence and performance by building a sense of shared social identity. *Journal of Experimental Psychology: Applied, 21*(1), 89.

Freling, T. H., & Forbes, L. P. (2005). An examination of brand personality through methodological triangulation. *Journal of Brand Management, 13*(2), 148–162.

Garbarino, E. C., & Edell, J. A. (1997). Cognitive effort, affect, and choice. *Journal of Consumer Research, 24*(2), 147–158.

Goodman, J. K., Broniarczyk, S. M., Griffin, J. G., & McAlister, L. (2013). Help or hinder? When recommendation signage expands consideration sets and heightens decision difficulty. *Journal of Consumer Psychology, 23*(2), 165–174.

Gretzel, U., & Fesenmaier, D. R. (2006). Persuasion in recommender systems. *International Journal of Electronic Commerce, 11*(2), 81–100.

Griol, D., Carbó, J., & Molina, J. M. (2013). An automatic dialog simulation technique to develop and evaluate interactive conversational agents. *Applied Artificial Intelligence, 27*(9), 759–780.

Gustafsson, A., Kristensson, P., & Witell, L. (2012). Customer co-creation in service innovation: a matter of communication?. *Journal of Service Management, 23*(3), 311-327.

Guthrie, S. E. (1997). Anthropomorphism: A definition and a theory. In R. Mitchell, Nicholas S. Thompson & H. L. Miles (Eds.), *Anthropomorphism, anecdotes, and animals.* Suny Press.

pp. 50–58 (1997)

Harmon-Jones, E. (2002). A cognitive dissonance theory perspective on persuasion. *The persuasion handbook: Developments in theory and practice,* 99–116.

Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science, 19*(1), 4–21.

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis second edition: A regression-based approach.* New York, NY: Guilford.

Haynes, G. A. (2009). Testing the boundaries of the choice overload phenomenon: The effect of number of options and time pressure on decision difficulty and satisfaction. *Psychology & Marketing, 26*(3), 204–212.

Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010). Assessing acceptance of assistive social agent technology by older adults: The Almere model. *International Journal of Social Robotics, 2*(4), 361–375.

Hill, J., Ford, W.E., & Farreras, I.G. (2015). Real conversations with artificial intelligence: a comparison between human-human online conversations and human-chatbot conversations. *Computers in Human Behavior*, 49, 245-250.

Holzwarth, M., Janiszewski, C., & Neumann, M. M. (2006). The influence of avatars on online consumer shopping behavior. *Journal of Marketing, 70*(4), 19–36.

Hong, S. M., & Giannakopoulos, E. (1994). The relationship of satisfaction with life to personality characteristics. *The Journal of Psychology*, *128*(5), 547–558.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172.

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

Johnson, D. I., & Acquavella, G. (2012). Organization-public relationship: Satisfaction and intention to retain a relationship with a cell phone service provider. *Southern Communication Journal, 77*(3), 163–179.

Keeling, K., McGoldrick, P., & Beatty, S. (2010). Avatars as salespeople: Communication style, trust, and intentions. *Journal of Business Research, 63*(8), 793–800.

Kent, R. J., & Allen, C. T. (1994). Competitive interference effects in consumer memory for advertising: the role of brand familiarity. *Journal of marketing*, *58*(3), 97-105.

Kiani, R., Corthell, L., & Shadlen, M. N. (2014). Choice certainty is informed by both evidence and decision time. *Neuron, 84*(6), 1329–1342.

Kwon, S. J., & Chung, N. (2010). The moderating effects of psychological reactance and product involvement on online shopping recommendation mechanisms based on a causal map. *Electronic Commerce Research and Applications, 9*(6), 522–536.

Lamberton, C. (2013). A spoonful of choice: How allocation increases satisfaction with tax payments. *Journal of Public Policy & Marketing, 32*(2), 223–238.

Larivière, B., Bowen, D., Andreassen, T. W., Kunz, W., Sirianni, N. J., Voss, C., . . . & De Keyser, A. (2017). "Service Encounter 2.0": An investigation into the roles of technology, employees and customers. *Journal of Business Research, 79*, 238–246.

Laroche, M., Kim, C., & Zhou, L. (1996). Brand familiarity and confidence as determinants of purchase intention: An empirical test in a multiple brand context. *Journal of Business Research, 37*(2), 115–120.

Lee, S., & Choi, J. (2017). Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity. *International Journal of Human-*

Computer Studies, 103, 95–105.

Lee, B. K., & Lee, W. N. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing, 21*(3), 159–183.

Lee, G., & Lee, W. J. (2009). Psychological reactance to online recommendation services. *Information & Management, 46*(8), 448–452.

Lefcourt, H. M., Hogg, E., Struthers, S., & Holmes, C. (1975). Causal attributions as a function of locus of control, initial confidence, and performance outcomes. *Journal of Personality and Social Psychology, 32*(3), 391.

Levy, A. R., Nicholls, A. R., & Polman, R. C. J. (2011). Pre-competitive confidence, coping, and subjective performance in sport. *Scandinavian Journal of Medicine & Science in Sports, 21*(5), 721–729.

Lombart, C., & Louis, D. (2012). Consumer satisfaction and loyalty: Two main consequences of retailer personality. *Journal of Retailing and Consumer Services, 19*(6), 644–652.

McGinty, L., & Smyth, B. (2006). Adaptive selection: An analysis of critiquing and preference-based feedback in conversational recommender systems. *International Journal of Electronic Commerce, 11*(2), 35–57.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research, 13*(3), 334–359.

Mild, A., & Reutterer, T. (2003). An improved collaborative filtering approach for predicting cross-category purchases based on binary market basket data. *Journal of Retailing and Consumer Services, 10*(3), 123–133.

Mills, J., Meltzer, R., & Clark, M. (1977). Effect of number of options on recall of information supporting different decision strategies. *Personality and Social Psychology Bulletin*, *3*(2), 213–218.

Mimoun, M. S. B., Poncin, I., & Garnier, M. (2012). Case study—Embodied virtual agents: An analysis on reasons for failure. *Journal of Retailing and Consumer Services*, *19*(6), 605–612.

Moon, H. (2001). Looking forward and looking back: Integrating completion and sunk-cost effects within an escalation-of-commitment progress decision. *Journal of Applied Psychology*, *86*(1), 104–113.

Mou, Y., & Xu, K. (2017). The media inequality: Comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior, 72*, 432–440.

Murano, P., & Holt, P. O. (2011). Evaluation of human-like anthropomorphism in the context of online bidding and affordances. *Journal of Computing*, *3*(6), 1–8.

Murphy, J., Gretzel, U., & Hofacker, C. (2017, May). Service robots in hospitality and tourism: Investigating anthropomorphism. In *15th APacCHRIE Conference* (Vol. 31).

Murphy, J., Hofacker, C., & Gretzel, U. (2017). Dawning of the age of robots in hospitality and tourism: challenges for teaching and research. *European Journal of Tourism Research, 15,* 104–111.

Murray, K. B., & Häubl, G. (2009). Personalization without interrogation: Towards more effective interactions between consumers and feature-based recommendation agents. *Journal of Interactive Marketing*, *23*(2), 138–146.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, *56*(1), 81–103.

Ng, I. C. L., & Vargo, S. L. (2018). Service-dominant (SD) logic, service ecosystems and institutions: Bridging theory and practice. *Journal of Service Management, 29* (4), 518–520.

Novemsky, N., Dhar, R., Schwarz, N., & Simonson, I. (2007). Preference fluency in choice. *Journal of Marketing Research, 44*(3), 347–356.

Nowak, K. L., & Rauh, C. (2008). Choose your "buddy icon" carefully: The influence of avatar androgyny, anthropomorphism and credibility in online interactions. *Computers in Human Behavior, 24*(4), 1473–1493.

Oliver, R. L. (2014). *Satisfaction: A Behavioral Perspective on the Consumer: A Behavioral Perspective on the Consumer*. Routledge.

Oliver, R. L., & DeSarbo, W. S. (1988). Response determinants in satisfaction judgments. *Journal of Consumer Research, 14*(4), 495–507.

Palmer, M. P. (1995). Interpersonal communication and virtual reality: Mediating interpersonal relationships. In F. Biocca and M. R. Levy (Eds.), *Communication in the age of virtual reality* (pp. 277–302). Hillsdale, NJ: Lawrence Erlbaum.

Pantano, E., Priporas, C. V., & Stylos, N. (2017). 'You will like it!' Using open data to predict tourists' attitude toward a tourist attraction. *Tourism Management, 60*, 430–438.

Park, C. H., & Kim, Y. G. (2003). Identifying key factors affecting consumer purchase behavior in an online shopping context. *International Journal of Retail & Distribution Management, 31*(1), 16–29.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker.* Cambridge: Cambridge University Press.

Peltier, J.W., Dahl, A., & Swan, E.L. (2020). Digital information flows across a B2C/C2C continuum and technological innovations in service ecosystems: a service-dominant logic perspective. *Journal of Business Research, forthcoming*, DOI: https://doi.org/10.1016/j.jbusres.2020.03.020.

Perfect, T. J. (2004). The role of self-rated ability in the accuracy of confidence judgements in eyewitness memory and general knowledge. *Applied Cognitive Psychology, 18*(2), 157–168.

Pornpitakpan, C. (2004). The persuasiveness of source credibility: A critical review of five decades' evidence. *Journal of Applied Social Psychology, 34*(2), 243–281.

Purington, A., Taft, J. G., Sannon, S., Bazarova, N. N., & Taylor, S. H. (2017, May). Alexa is my new BFF: Social roles, user satisfaction, and personification of the amazon echo. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 2853–2859). ACM.

PWC Global Consumer Insights. (2018), Available at: https://www.pwc.com/gx/en/industries/consumer-markets/consumer-insights-survey/artificial-intelligence.html

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.

Quick, B. L., Scott, A. M., & Ledbetter, A. M. (2011), A close examination of trait reactance and issue involvement as moderators of psychological reactance theory. *Journal of Health Communication, 16*(6), 660–679

Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science,* 33(2), 206-221.

Satzger, B., Endres, M., & Kießling, W. (2006, September). A preference-based recommender system. In *International Conference on Electronic Commerce and Web Technologies* (pp. 31–40). Springer, Berlin, Heidelberg.

Seeger, A. M., & Heinzl, A. (2018). Human versus machine: Contingency factors of anthropomorphism as a trust-inducing design strategy for conversational agents. In *Information systems and neuroscience* (pp. 129–139). Springer, Cham.

Shafir, E., Simonson, I., & Tversky, A. (1993). Reason-based choice. *Cognition, 49*(1–2), 11–36.

Shen, L. (2015). Antecedents to psychological reactance: The impact of threat, message frame, and choice. *Health Communication, 30*(10), 975–985.

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.

Stock, R. M., & Merkle, M. (2018). Can humanoid service robots perform better than service employees? A comparison of innovative behavior cues. In *Proceedings of the 51st Hawaii International Conference on System Sciences 2018,* 1056–1065.

Su, Y., & Klein, J. D. (2006). Effects of navigation tools and computer confidence on performance and attitudes in a hypermedia learning environment. *Journal of Educational Multimedia and Hypermedia, 15*(1), 87–106.

Sweeney, J. C., Hausknecht, D., & Soutar, G. N. (2000). Cognitive dissonance after purchase: A multidimensional scale. *Psychology & Marketing, 17*(5), 369–385.

Tsiros, M., Mittal, V., & Ross Jr, W. T. (2004). The role of attributions in customer satisfaction: A reexamination. *Journal of Consumer Research, 31*(2), 476–483.

Valenzuela, A., Dhar, R., & Zettelmeyer, F. (2009). Contingent response to self-customization procedures: Implications for decision satisfaction and choice. *Journal of Marketing Research, 46*(6), 754–763.

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: when does the message get through? *Computers in Human Behavior*, 98, 150-157.

Vannucci, V., & Pantano, E. *(in press.)*. Digital or human touchpoints? Insights from consumer-facing in-store services. *Information Technology and People.*

Vargo, S. L., & Lusch, R. F. (2017). Service-dominant logic 2025. *International Journal of Research in Marketing,* 34(1), 46–67.

Verhagen, T., van Nes, J., Feldberg, F., & van Dolen, W. (2014). Virtual customer service agents: Using social presence and personalization to shape online service encounters. *Journal of Computer-Mediated Communication, 19*(3), 529–545.

Wang, Q., & Shukla, P. (2013). Linking sources of consumer confusion to decision satisfaction: The role of choice goals. *Psychology & Marketing, 30*(4), 295–304.

Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human? The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science, 5*(3), 219–232.

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology, 52,* 113–117.

White, T. B., Zahay, D. L., Thorbjørnsen, H., & Shavitt, S. (2008). Getting too personal: Reactance to highly personalized email solicitations. *Marketing Letters, 19*(1), 39–50.

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.

Woodman, T. I. M., & Hardy, L. E. W. (2003). The relative impact of cognitive anxiety and self-confidence upon sport performance: A meta-analysis. *Journal of Sports Sciences, 21*(6), 443–457.

Yee, N., Bailenson, J. N., & Rickertsen, K. (2007, April). A meta-analysis of the impact of the inclusion and realism of human-like faces on user experiences in interfaces. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 1–10). ACM.

Yoo, W-S., Lee, Y., & Park, J. K. (2010). The role of interactivity in e-tailing: Creating value and increasing satisfaction. *Journal of Retailing and Consumer Services,17* (2), 89–96.

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., Bricman, M., & Jessenitschnig, M. (2011). Cost-effective development of virtual sales assistants. In E. Damiani, J. Jeong, R. J. Howlett, & L.C. Jain (Eds.), New directions in intelligent multimedia systems and services (pp.1–11). Berlin-Heidelberg: Springer-Verlag.

Zhang, T., Kaber, D. B., Zhu, B., Swangnetr, M., Mosaly, P., & Hodge, L. (2010). Service robot feature design effects on user perceptions and emotional responses. *Intelligent Service Robotics, 3*(2), 73–88.

Złotowski, J., Proudfoot, D., Yogeeswaran, K., & Bartneck, C. (2015). Anthropomorphism: Opportunities and challenges in human–robot interaction. *International Journal of Social Robotics, 7*(3), 347–360.

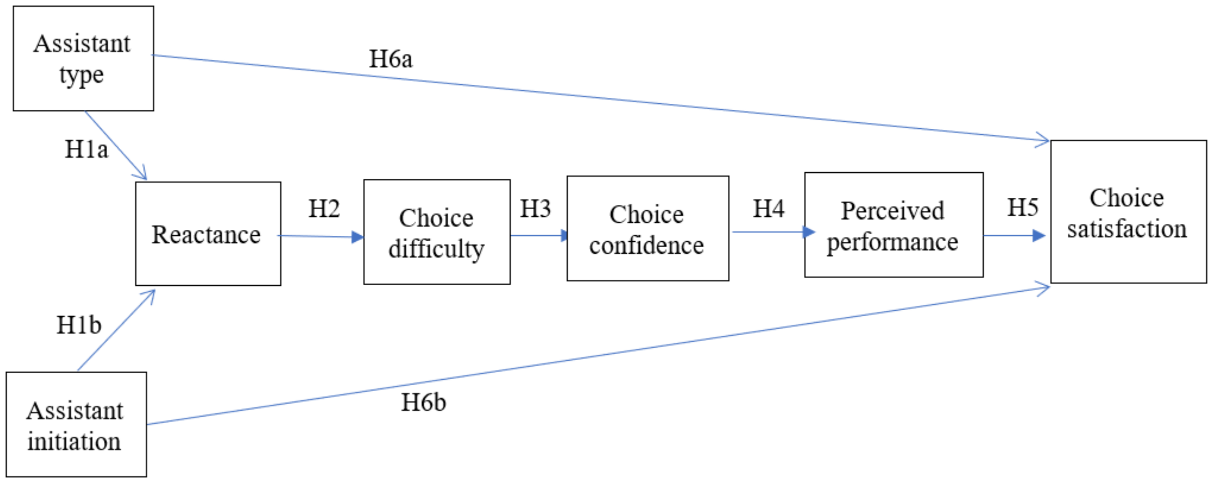
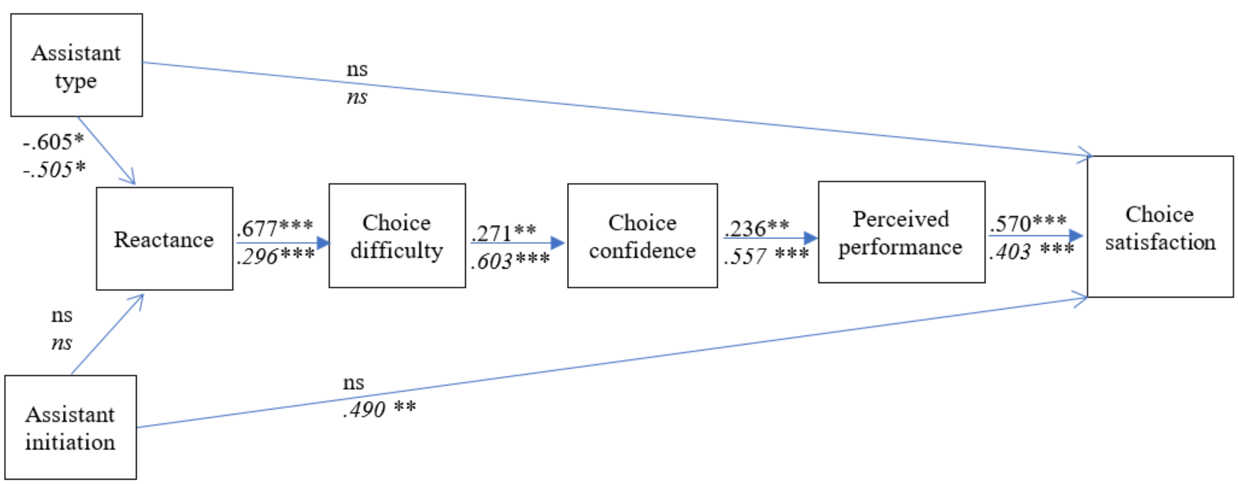


Fig. 1. Conceptual model.

Fig. 2. Theoretical model with estimates.



*Italics = Study 2; * p* ≤ .05; ** *p* ≤ .01; *** *p* ≤ .001

Table 1.
Sequential mediation analysis from assistant type and initiation to choice satisfaction.

	Study	Coeff.	se	*t*	*p*	LLCI	ULCI
H1a: Assistant type on reactance	S1	−.605	.277	−2.183	.031	−1.153	−.057
	S2	*−.505*	*.243*	*-2.073*	*.039*	*-.985*	*-.024*
H1b: Assistant initiation on reactance	S1	−.074	.282	−.264	.792	−.632	.483
	S2	*−.406*	*.239*	*1.695*	*.100*	*−.067*	*.880*
H1c: Type × Initiation on reactance	S1	.632	.315	2.004	.047	.008	1. 256
	S2	*.689*	*.340*	*−2.027*	*.044*	*.017*	*1.36*
H2: Reactance on choice difficulty	S1	.677	.064	10.578	.000	.550	.803
	S2	*.296*	*.089*	*3.322*	*.001*	*.120*	*.472*
H3: Choice difficulty on choice certainty	S1	.271	.098	2.760	.007	.077	.465
	S2	*.603*	*.077*	*7.797*	*.000*	*.450*	*.756*
H4: Choice certainty on perceived performance	S1	.236	.067	3.491	.007	.102	.397
	S2	*.557*	*.069*	*8.109*	*.000*	*.421*	*.693*
H5: Perceived performance on choice satisfaction	S1	.570	.058	9.918	.000	.456	.684
	S2	*.403*	*.047*	*8.631*	*.000*	*.311*	*.495*
H6a: Assistant type on choice satisfaction	S1	.103	.125	.822	.412	−.144	.349
	S2	*.291*	*.183*	*1.588*	*.114*	*−.071*	*.654*
H6b: Assistant initiation on choice satisfaction	S1	−.065	.122	−.530	.597	−.305	.176
	S2	*.489*	*.181*	*2.711*	*.008*	*.133*	*.847*

Note: LLCI = Lower limit confidence interval; ULCI = Upper limit confidence interval

APPENDIX

OPTION	SERVICE PROVIDER	MINUTES	SMS	INTERNET	PRICE (per month)
A	vodafone	1000	1000	5 GB	$10
B	vodafone	1000	1000	10 GB	$15
C	vodafone	UNLIMITED	UNLIMITED	10 GB	$30
D	vodafone	100	50	4 GB	$9
E	TIM	UNLIMITED	0	0	$5
F	TIM	1000	0	20 GB	$10
G	3	UNLIMITED	1000	100 GB	$19
H	3	1000	1000	10 GB	$7
I	coop voce	200	200	2 GB	$5
L	WIND	1000	500	20 GB	$10
M	WIND	UNLIMITED	500	5 GB	$12
N	3	UNLIMITED	1000	20 GB	$15
O	TIM	0			
P	Poste mobile	250			
Q	Poste mobile	1000			

Fig. A1. Stimuli examples: Anthropomorphic system-initiated digital assistant (Study 1).

CHOOSE YOUR CAR!

CAR MODEL	PROVIDER	DAMAGE EXCESS	DEPOSIT AT PICK-UP	CAR TYPE	PRICE/DAY
A Ford Focus	Europcar	500 £	0 £	Medium	42£
B BMW 3 Series Estate	Europcar	700 £	0 £	Estate	69 £
C Ford Focus Estate	Europcar	0 £	0 £	Estate	52 £
D Ford Fiesta	Europcar	750£	750 £	Small	26£
E Fiat 500	AVIS	0 £	750 £	Small	22£
F Nissan Qashqai	AVIS	700 £	750 £	SUVs	40 £
G Renault Captur	enterprise	0 £	0 £	SUVs	35 £
H Opel Astra Estate	enterprise	500 £	0 £	Estate	37 £
I Volkswagen Polo	SIXT	1,000 £	750 £	Small	26£
L Volkswagen Tiguan	Hertz	800 £	250 £	SUVs	48 £
M Opel Astra	Hertz	0 £	250 £	Medium	27£
N Nissan Qashqai	enterprise	0 £	0 £	SUVs	46 £
O Ford Fiesta	AVIS	1,500£	750 £	Small	30£
P Ford Focus	GOLDCAR	500 £	500 £	Medium	39£
Q Ford Focus Estate	GOLDCAR	500 £	750 £	Estate	43 £

Fig. A2. Stimuli examples: Non-anthropomorphic user-initiated digital assistant (Study 2).

Table A.1
Construct measures and results of confirmatory factor analysis.

Measures	Study	CR	AVE	Cronbach alpha
Reactance	S1:	.90	.75	.90
	S2:	.81	.58	.84
Recommending the tariff / car rental plans restricts my choice				
Recommending the tariff / car rental plans hinders in my choice.				
Recommending the tariff / car rental plans intervenes in my free choice				
Choice difficulty	S1:	-	-	-
	S2:	.77	.52	.70
The decision was difficult				
I am likely to regret my decision				
Selecting a tariff / car rental plan from this website was simple (R)				
Choice confidence	S1:	.79	.66	.76
	S2:	.88	.79	.95
I am confident about my evaluation of each option				
I am certain about each option				
Perceived performance	S1:	.84	.64	.83
	S2:	.94	.85	.94
The digital assistant improved my performance				
The digital assistant was useful for my task				
The digital assistant helped me to take a better decision by giving me access to higher quality information.				

Choice satisfaction	S1:	-	-	-
	S2:	.84	.52	.80
I found the process of deciding the tariff plan / car to rent frustrating				
Several good option were available for me to choose between				
I am satisfied with the experience of deciding which tariff plan / car to choose				
I think that the choice selection was good				
I would be happy to choose from the same set of options on my next occasion				
I found the process of deciding which tariff plan / car to choose interesting				
User Experience				
	S1:	-	-	-
	S2:	.82	.53	.81
This webpage's capabilities met my requirements				
Using this webpage was a frustrating experience				
I had to spend too much time checking things with this webpage				
This webpage is easy to use				
Familiarity				
	S1:	-	-	-
	S2:	.79	.65	.73
Familiar / Unfamiliar				
Inexperienced/ Experienced				
Knowledgeable/ Not Knowledgeable				

Note. CR = composite reliability; AVE = average variance extracted.

Table A.2
Means, standard deviations, and squared correlations.

Variable	Study	Mean	SD	1	2	3	4	5	6
1 Reactance	S1	3.46	1.73	1.00	.42	.01	.06	.11	-
	S2	3.55	1.15	1.00	.05	.01	.01	.01	.02
2 Choice difficulty	S1	2.74	1.63	.42	1.00	.07	.06	.12	-
	S2	3.05	1.21	.05	1.00	.30	.23	.40	.42
3 Choice certainty	S1	4.71	1.41	.01	.07	1.00	.04	.04	-
	S2	4.63	1.37	.01	.30	1.00	.28	.36	.25
4 Perceived performance	S1	5.56	1.14	.06	.06	.04	1.00	.42	-
	S2	4.89	1.40	.01	.23	.28	1.00	.37	.41
5 Choice satisfaction	S1	5.65	1.01	.11	.12	.04	.42	1.00	-
	S2	4.87	1.01	.01	.40	.36	.37	1.00	.35
6 User Experience	S1	-	-	-	-	-	-	-	
	S2	5.01	1.21	.01	.42	.25	.51	.35	1.00

Note. SD = standard deviation.