Persuasive agents

Unraveling the persuasive potential of conversational agents

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Publication date
2022

CHAPTER 2

"I am here to assist you today": The role of entity, interactivity and experiential perceptions in chatbot persuasion

This chapter is published as:
Ischen, C., Araujo, T. B., van Noort, G., Voorveld, H. A. M., & Smit, E. G. (2020).
"I Am Here To Assist You Today":
The Role of Entity, Interactivity and Experiential Perceptions in Chatbot Persuasion.
Journal of Broadcasting & Electronic Media,
64(4), 615-639.
https:/doi.org/10.1080/08838151.2020.1834297

Online users are increasingly exposed to chatbots as one form of AI-enabled media technologies, employed for persuasive purposes, e.g., making product/service recommendations. However, the persuasive potential of chatbots has not yet been fully explored. Using an online experiment (n = 242), we investigate the extent to which communicating with a stand-alone chatbot influences affective and behavioral responses compared to interactive Web sites. Several underlying mechanisms are studied, showing that enjoyment is the key mechanism explaining the positive effect of chatbots (vs. Web sites) on recommendation adherence and attitudes. Contrary to expectations, perceived anthropomorphism seems not to be particularly relevant in this comparison.

The communication between online users and organizations is increasingly shifting toward interactions with technology driven by artificial intelligence (AI; Sundar, 2020). Among the most prevalent instances of technology with which users are confronted are AI-based chatbots. Defined as "software that accepts natural language as input and generates natural language as output, engaging in a conversation" (Griol et al., 2013, p. 706), chatbots can be found on social media (e.g., Facebook, Twitter) and messaging apps (e.g., Skype, Facebook Messenger); they can be an alternative to (branded) Web sites (e.g., A.s.r., 2019). These stand-alone chatbots are often used for making product or service recommendations (e.g., shopping, financial/health-related decisions; CX Company, 2019; Dialogflow, 2019; Nguyen, 2017; Spence, 2019), and the global chatbot market is growing (Grand View Research, 2017). This is reflected in the number of chatbot users. In the 2018 state of chatbot report, 12% of U.S. online users reported having communicated with chatbots during the last 12 months (Drift, 2018); and a survey of the Dutch adult population found that 47% of the respondents had perceivably interacted with a chatbot from a brand (Araujo et al., 2019).

Chatbots resembling a stand-alone chat interface can be considered as a separate entity in our communication environment influencing user responses (Guzman, 2019; Peter & Kühne, 2018; Zhao, 2006). These responses to chatbots have been studied in the field of human-machine communication and focus mostly on users' social responses to the chatbot as a communicating entity, rather than on persuasion (Fogg, 2002; Go & Sundar, 2019; Mou & Xu, 2017; Nass & Moon, 2000; Reeves & Nass, 1996). Strikingly, the persuasive consequences of chatbots as a new communication source are yet to be (fully) explored. The first aim of this study is therefore to investigate the affective and behavioral persuasive outcomes of user engagement with chatbots as AI-enabled media technologies, compared to interactive Web sites, a more traditional form of interactive media in a service recommendation context.

Separate research lines regarding interactive Web sites and chatbots have shown that several underlying mechanisms play an important role for user responses. These are communication entity perceptions, based on social response theory (Reeves & Nass, 1996) and social presence theory (Short et al., 1976); perceptions of interactivity, based on interactivity theories (e.g., Sundar, 2012); and different immediate experiential perceptions (e.g., Nabi & Krcmar, 2004). However, the extent to which these mechanisms influence user perceptions as interactions move from interactive Web sites to stand-alone AI-driven chatbots remains an open question. The second aim of this study is therefore to combine these three different types of mechanisms that might (in parallel) explain users' recommendation adherence and attitudes toward recommendation, medium, and organization.

Finally, this study aims to capture a possible interplay of different, perhaps even conflicting, sources in a digital recommendation setting (Guzman, 2019). We not only distinguish the source of communication (stand-alone chatbot vs. interactive Web site), but we also focus on the origin of recommendation. Though such a recommendation can be based on human expertise, it can also be based on algorithms, scripts for mathematical calculation by the technology itself (Guzman, 2019; Logg, 2017; Sundar & Nass, 2000; Thurman et al., 2018). Based on the idea of a possible interplay of different sources for a digital recommendation, we propose the impact of the source of communication to be moderated by the origin of the recommendation (informed by a human expert vs. an algorithm).

Chatbots as a new communication source

Chatbots reshape today's media environment and thereby move the communication science field from computer-mediated communication into human-machine communication (Guzman, 2019; Peter & Kühne, 2018; Zhao, 2006). While digital media previously enabled interactions in which the user communicated with an organization through a medium, a stand-alone chatbot can appear as a communicating entity instead, especially when enabled by AI (Fogg, 2002; Mou & Xu, 2017). In doing so, interacting with a chatbot as an entity might fundamentally differ from using an interactive Web site, even if the retrieved information is the same (Zhao, 2006).

Previous scholars have pointed toward the importance of contingency in message interactivity, i.e., the systematic relatedness of later messages with earlier ones in a communication sequence (Rafaeli, 1988; Sundar, 2012; Sundar et al., 2016, 2003) when examining contingency cues in chatbots only (e.g., Lew et al., 2018) or a chatbot as an addition to a Web site (e.g., Sundar et al., 2016). However, as user interactions move from interactive Web sites to stand-alone chatbots, contingency is potentially present in both interfaces – as the user input and the (stand-alone chatbot or interactive Web site) output have a systematic relationship and are built upon each other. As such, this study aims to contribute to this stream of research by focusing on the perceptions about the source (i.e., source orientation) instead.

In drawing this direct comparison between chatbot and interactive Web site, we therefore identify differences in source orientation as a distinguishing feature and as an important determinant for user reactions (Sundar et al., 2016; Sundar & Nass, 2000). The idealization of a chatbot as a fully responsive entity engaging in a back-and-forth dialogue might influence user perceptions of the communicating source and of the message, independently of the message content (Sundar et al., 2016). Most notably, in the interaction, the chatbot itself – rather than the organization behind it – may be

perceived as the source of communication. As a result, according to the MAIN-model (arguing how modality, agency, interactivity, and navigability influence credibility judgments), the communicating source can function as a cue that triggers the use of mental shortcuts – heuristics – that enable an effortless assessment and attitude formation, especially in situations in which it is difficult to form evaluations (Sundar, 2008).

We argue that chatbots possess characteristics that trigger agency heuristics. *Agency* is hereby defined as "the capability to autonomously perform self-directed behaviors" (Banks, 2019, p. 364; Himma, 2009). Thus, by displaying agency, a source is perceived as being in charge of the communication and taking responsibility for the information provided (Nowak & Biocca, 2003). As shown in previous research, users are indeed influenced by product recommendations made by sources embedded in an online environment (e.g., recommender systems; D. R. Liu & Shih, 2005; Qiu & Benbasat, 2010; Senecal & Nantel, 2004). These perceptions involve presumptions of certain abilities of the source that can invoke, for example, a social presence heuristic (perception of communicating with a social entity), which can subsequently influence user perceptions. Importantly, these might not only include perceptions of the source itself (chatbot/Web site) and the organization behind it, but also the recommendation irrespective of the message content (Sundar, 2008).

Given the current study context, it is unknown the extent to which interacting with a stand-alone chatbot might increase or decrease recommendation adherence and positive attitudes, as compared to an interactive Web site. Therefore, we draw on a variety of theories and bodies of literature to develop a set of underlying mechanisms that may explain user responses. We first include perceptions of the communication entity in our model, drawing on different lines of research, including the Computers Are Social Actors (CASA) paradigm (Reeves & Nass, 1996) and social presence theory (Short et al., 1976). Second, based on the vast body of research on message interactivity (Sundar, 2012), we include dimensions of perceived interactivity as underlying mechanisms to examine whether different sources possess the ability to influence perceptions of interactivity, independent of message content. Thirdly, we add enjoyment and perceived intrusiveness, summarized as experiential perceptions, to our model, since they play an important role for user engagement with interactive media (Bellur & Sundar, 2017; Oh & Sundar, 2015). Within these types, there may be parallel mechanisms at place, the first expectedly leading to higher levels of recommendation adherence and positive attitudes and the other two types leading to either higher or lower levels of persuasion. The conceptual model is shown in Figure 1.

The role of entity perceptions

Perceptions of the communicating entity are expected to influence persuasion. The CASA paradigm states that humans tend to respond socially to computers similarly to how they would respond to other humans, even when they are aware of their interaction with technology (Nass & Moon, 2000; Reeves & Nass, 1996). One explanation is that humans are socially oriented, showing social responses toward a technology imbued with humanlike characteristics (Chattaraman et al., 2019; Moon, 2000). Consequently, the first underlying mechanism explored in this study is anthropomorphism. While mindful anthropomorphism is the conscious evaluation of human or machine-likeness (Kim & Sundar, 2012), anthropomorphism can also be a mindless process in which "humanlike properties, characteristics, or mental states" are attributed to either real, but also imagined nonhuman agents and objects (Epley et al., 2007, p. 865). Previous studies found that anthropomorphism can be triggered by cues on (interactive) Web sites (Kim & Sundar, 2012) and also displayed by chatbots (Araujo, 2018). Since a chatbot appears as a communication entity that autonomously interacts in a dialogical manner, users are more likely to anthropomorphize a chatbot in comparison to a Web site. The social behavior triggered by anthropomorphism can in turn lead to more trust, leading to more positive responses such as attitudes in general (de Visser et al., 2016). We therefore propose the following hypothesis:

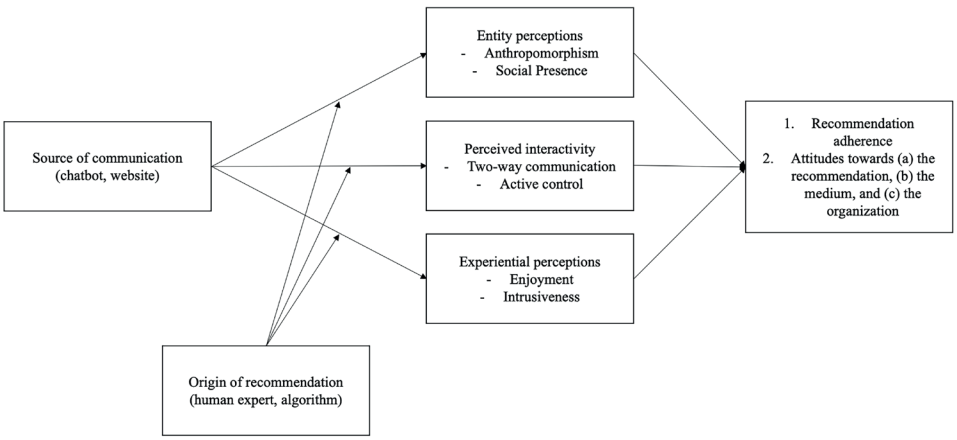

Figure 1. Conceptual Model

H1a. Receiving a product recommendation from a chatbot (versus Web site) leads to higher anthropomorphism, subsequently leading to (1) higher recommendation adherence, and (2) more positive attitudes toward (a) the recommendation, (b) the medium, and (c) the organization.

It is important to note that literature often distinguishes between anthropomorphism and the concept of social presence, seeing them as two separate concepts. Though anthropomorphism taps into attribution of humanlikeness, or humanlike characteristics or personalities, social presence implies that a medium is perceived as a "real" social interaction partner with less emphasis on the role of technology (Araujo, 2018; Kim & Sundar, 2012; Xu & Lombard, 2017). We argue that, even though both interactive Web sites and chatbots are generally able to influence the perception of social presence (for social presence on Web sites, see Gefen & Straub, 2004), social presence will be higher for a chatbot than for a Web site because a chatbot positions itself more directly as an actual interaction partner (in a dialog) than a Web site. As social presence gives the user a sense of human warmth and sociability – which in turn can lead to more favorable attitudes (Gefen & Straub, 2004; Hassanein & Head, 2007; Qiu & Benbasat, 2009; Shih, 2004) – we propose the following hypothesis:

H1b. Receiving a product recommendation from a chatbot (versus Web site) leads to higher social presence, subsequently leading to (1) higher recommendation adherence, and (2) more positive attitudes toward (a) the recommendation, (b) the medium, and (c) the organization.

The role of perceived interactivity

Attributes of interactivity have been shown to influence outcomes such as interpersonal attraction and satisfaction (Lew et al., 2018), engagement (e.g., feelings of enjoyment), attitudes, and behavioral intentions in a health-related context (Bellur & Sundar, 2017; Oh & Sundar, 2015). Moreover, a recent meta-analysis showed that perceived interactivity in particular (rather than interactive media attributes) was effective in shaping user responses such as positive attitudes and behavioral intentions (Yang & Shen, 2018). Translating these previous findings into our direct comparison of chatbot and Web site, two dimensions of perceived interactivity are important. These are perceived two-way communication and perceived active control. While perceived two-way communication is defined as the perception of reciprocal communication, perceived active control refers to users' perceived ability to oversee and control the interaction with a medium (Y. Liu & Shrum, 2009; Voorveld et al., 2011). Previous

research showed that higher levels of both dimensions result in more positive attitudes (e.g., Fiore et al., 2005; Macias, 2003; van Noort et al., 2012).

Based on the theoretical explication of message interactivity (Sundar et al., 2016), both chatbot and interactive Web site possess interactive media attributes that influence the different dimensions of perceived interactivity. We propose, however, that the responsiveness of a chatbot as an entity might lead to higher perceived two-way communication than receiving information from a Web site, leading us to explore the following research question:

> **RQ1a.** Does receiving a product recommendation from a chatbot (versus Web site) lead to higher perceived two-way communication, subsequently leading to (1) higher recommendation adherence, and (2) more positive attitudes toward (a) the recommendation, (b) the medium, and (c) the organization?

Whereas the user is in control of the flow of giving and retrieving information when interacting with a Web site, the chatbot itself might be perceived as leading the conversation in chatbot-based interactions, especially when it asks a series of sequential questions. To explore this mechanism, we propose the following research question:

> **RQ1b.** Does receiving a product recommendation from a chatbot (versus Web site) lead to lower perceived active control, subsequently leading to (1) lower recommendation adherence, and (2) less positive attitudes toward (a) the recommendation, (b) the medium, and (c) the organization?

The role of experiential perceptions

The last underlying mechanisms explored in this study are experiential perceptions of the interaction (Nabi & Krcmar, 2004). Previous research suggests that the valence of such perceptions explains persuasion outcomes (Baek & Morimoto, 2012; Hassanein & Head, 2007). We argue that chatbot interactions, in comparison to a Web site, induce both positive and negative perceptions. First, because it is coming from a separate communication entity engaging in a back-and-forth dialogue, the interaction with a chatbot can lead to higher enjoyment of the interaction. Enjoyment, defined as perceiving a medium as enjoyable in its own right (Carrol & Thoma, 1988; Hassanein & Head, 2007), has been shown to positively influence user attitudes online (Hassanein & Head, 2007; M. K. O. Lee et al., 2005).

Contrastingly, the interaction with a chatbot can also be perceived as more intrusive. Chatbots display agency and may invade personal space, thereby interfering with an individual's cognitive process (Li et al., 2002; Morimoto & Chang, 2006). This may lead to perceptions of being "uninvited" in the conversation (Fournier & Avery, 2011) and consequently to higher intrusiveness (Leray & Sansonnet, 2007). In this case, a source acting less autonomously like a Web site would be more persuasive, leading to the following hypotheses:

H2a. Receiving a product recommendation from a chatbot (versus Web site) leads to higher enjoyment, subsequently leading to (1) higher recommendation adherence, and (2) more positive attitudes toward (a) the recommendation, (b) the medium, and (c) the organization.

H2b. Receiving a product recommendation from a chatbot (versus Web site) leads to higher perceived intrusiveness, subsequently leading to (1) lower recommendation adherence, and (2) less positive attitudes toward (a) the recommendation, (b) the medium, and (c) the organization.

The moderating effect of origin of recommendation (human expert vs. algorithm)

The persuasive effects of interacting with a chatbot as compared to a Web site arguably also depend on the origin of the recommendation. A recommendation can originate from a human source, e.g., a human expert, or can be based on technology, e.g., calculated by an algorithm. Thus, the recommendation origin may differ, independent of the communicating source, adding to a phenomenon that Sundar (2008, p. 73) describes as "a multiplicity of sources," meaning that the perception of sources in digital communication is often indistinct (Sundar & Nass, 2000).

Depending on the perceived origin of the recommendation, different heuristics are triggered. In this case, the heuristic that the information is generated by a machine (i.e., machine heuristic) implies an objective and rational selection of information free from ideological bias (Dijkstra et al., 1998; Sundar, 2008; Thurman et al., 2018). Therefore, the framing of a message as an algorithmic recommendation might trigger a machine heuristic in comparison to a recommendation based on a human. For example, Senecal and Nantel (2004) examined whether different origins of recommendations (i.e., online recommender systems, human experts, other users) influence online-product choices and showed that an origin labeled as "recommender system" was most influential due to its perceived personalization possibilities. An algorithm as the origin of recommendation is thus hypothesized to strengthen the proposed persuasion processes.

More specifically, we hypothesize that the origin of recommendation moderates the effect of source of communication on the three underlying mechanisms. A chatbot as the source of communication and an algorithm as the origin of recommendation could lead to additive effects that may contribute to users' perceptions of an autonomously communicating interaction partner (Corti & Gillespie, 2016), leading to the following hypothesis:

H3. The effect of receiving a product recommendation from a chatbot (versus Web site) on (a) perceptions of the entity, (b) perceptions of interactivity, and (c) experiential perceptions is stronger when the origin of recommendation is an algorithm (vs. human expert), subsequently influencing (1) recommendation adherence, and (2) attitudes toward (a) the recommendation, (b) the medium, and (c) the organization.

METHOD

Design and sample

To test the hypotheses, an experimental study implementing a 2 (Communication source: chatbot vs. Web site) x 2 (Recommendation origin: based on human expert vs. algorithm) between-subjects design was conducted. Participants were recruited through an ISO-certified panel research company, using quotas for age and gender to reflect the Dutch population. Of 440 participants who completed the questionnaire, 21 were excluded because they did not speak English proficiently, 153 failed the attention check, and 24 spent less than five minutes on the questionnaire. This resulted in a final sample of 242 participants between 18 and 77 years old (M = 44.31, SD = 15.04), 49.2% female. In terms of education, 55.8% indicated they had a high educational level (middle: 34.7%; low: 9.5%).

Stimuli

The source of communication was manipulated in terms of the medium of interaction. Participants were asked to interact either with an interactive Web site or with a stand-alone chatbot. The Web site was designed in such a way that participants actively filled in information in an open-ended answer field and as a result received a recommendation displayed on the Web site. It resembled an online form as commonly presented on Web sites. The chatbot was created as a stand-alone platform, using a tool kit for conversational agent research (Araujo, 2020). It resembled an entirely text-based chat interface; it was thus not embedded in a Web site. The chatbot presented

itself in the chat window as an assistant helping to find a health insurance product. As previous research showed gender-stereotypical responses to computers, we assigned the gender-neutral name "Sam" to the chatbot (Nass et al., 1997). No other visual cues were used. The questions asked and information provided were similar across conditions. Examples of the stimulus material are provided in Figure 2, and the full dialogue is presented in Appendix A.

The origin of recommendation was manipulated by way of message content. In the human expert condition, participants were told that human experts have developed a choice model to give a recommendation, based on professional experience with customers. In the algorithm condition, participants were told that an algorithm calculates the best choice. Participants received this information twice during the interaction: at the beginning to explain the goal of the interaction and when receiving the recommendation.

Procedure

Randomly assigned to conditions, and after providing their informed consent, participants were asked to interact either with the chatbot or with the interactive Web site to receive a recommendation for a health insurance. Health insurance plans were chosen because they are mandatory in the Netherlands, and the choice of insurance package often depends on individual characteristics and preferences. Participants were instructed to answer a series of questions about their demographics (i.e., age, gender, place of residence) and their preferences (i.e., current health insurance

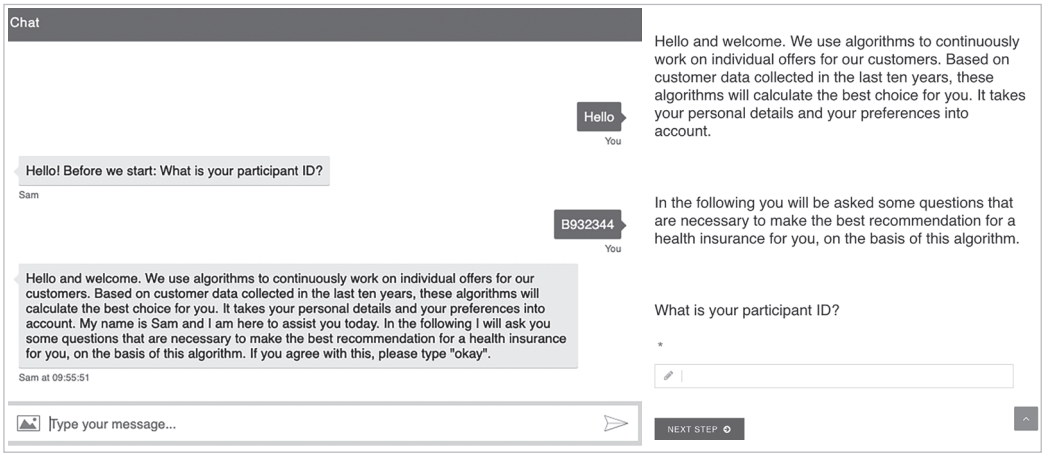

Figure 2. Stimulus material, interface examples of chatbot (left) and interactive website (right)

company, importance of customer service and travel behavior, budget), as well as two more intrusive questions (legal residence in the Netherlands and whether they had multiple sexual partners in the previous six months). Participants were instructed to follow the conversation flow without needing to answer sensitive questions, any input was accepted, including "I don't want to answer." In the Web site condition, participants were asked to fill in the information on the Web site, similar to an online form. In the chatbot condition, participants engaged in a chat conversation to answer the questions. Afterwards, all participants received the same recommendation for the (fictitious) health insurance company "ZorgPlus" (English: "CarePlus"), either provided by the Web site or by the chatbot. On average, participants interacted for 3.83 minutes (*SD* = 2.83) with the chatbot or Web site.

Pretest and pilot test

Since the chatbot and Web site were specifically developed for the study, several pretests were conducted to ensure that they functioned smoothly and that materials were perceived as intended. Based on the results of the pretest, the number and wording of the questions and the response time of the chatbot were adapted. A pilot test with a sample of 77 bachelor-level students (gender: 81.8% female; age: *M* = 20.36, *SD* = 2.33) showed significant correlations of chatbot/Web site condition and most of the mediators and outcome variables.

Measures

Unless stated otherwise, all items were measured on 7-point Likert-scales.[1] A list of all items is provided in Appendix B.

Mediators

Anthropomorphism. Mindful anthropomorphism was adapted from Powers and Kiesler (2006) using three 7-point semantic differential scales, e.g., "I perceived the chatbot/Web site as humanlike/machinelike" (*M* = 3.88, *SD* = 1.41, α = .94). Mindless anthropomorphism was measured with four items adapted from Kim and Sundar (2012), e.g., "I perceived the chatbot/ Web site as sociable" (*M* = 4.53, *SD* = 1.16, α = .92). **Social Presence.** Social presence was adapted from K. M. Lee et al. (2006), e.g., "While

[1] As part of this project, we further measured trust/trustworthiness, resistance, involvement, relevance, and privacy concerns. These measures were not used in this or other publications.

I was interacting with this chatbot/Web site, I felt as if it was an intelligent being" (*M* = 4.48, *SD* = 1.07, α = .90). The variables social presence, mindful anthropomorphism and mindless anthropomorphism are highly correlated ($r > .70$, $p < .01$). A principal component analysis with Varimax rotation yielded one factor with an eigenvalue greater than one, explaining a total of 64.03% of the variance.

Perceived Interactivity. Perceived active control was measured with a part of the interactivity scale used by Voorveld et al. (2011) with three items, including "I feel that I have a great deal of control over my experience using the chatbot/Web site" (*M* = 4.80, *SD* = 1.12, α = .72). Perceived two-way communication was measured with four items, including "The chatbot/Web site enables conversation" (*M* = 4.54, *SD* = 1.24, α = .89).

Enjoyment. Enjoyment was measured with four items adapted from Hassanein and Head (2007), including "I found the interaction with the chatbot/Web site entertaining" (*M* = 4.81, *SD* = 1.23, α = .93).

Intrusiveness. Intrusiveness was measured with seven items adapted from Li et al. (2002), including "I think the interaction with the chatbot/Web site was disturbing" (*M* = 2.89, *SD* = 1.03, α = .93).

Outcome variables

Recommendation Adherence. Recommendation adherence was measured with four items adapted from Dabholkar and Sheng (2012), including "It is very likely that I would buy the recommended insurance" (*M* = 3.83, *SD* = 1.08, α = .81).

Attitudes. To measure attitude toward the medium, items were adapted from Becker-Olsen (2003). Five semantic differential scale items were used, e.g., "I think the chatbot/Web site is good/bad" (*M* = 4.79, *SD* = 1.16, α = .94). Furthermore, we specifically asked about the recommendation given by the chatbot/Web site using the same sematic differential scale items, e.g., "I think the recommendation is good/bad" (*M* = 4.66, *SD* = 1.15, α = .95). Lastly, we asked about the health insurance company as the organization giving the recommendation, e.g., "I think the health insurance company is good/bad" (*M* = 4.67, *SD* = 1.00, α = .95).

Control variables

Familiarity with interactions with chatbots/Web sites and familiarity with health insurance were measured with two items adapted from Zhou et al. (2010), e.g., "Interacting with a chatbot/Web site is very familiar to me" (*M* = 5.08, *SD* = 1.26, α = .86) and "Health insurance is very familiar to me" (*M* = 5.19, *SD* = 1.05, α = .86).

Randomization check

Familiarity with insurance plans, age, gender, and education did not significantly differ across conditions. Familiarity with the medium was significantly different for chatbots and Web sites, $t(240) = -6.57$, $p < .001$. Participants were more familiar with Web sites ($M = 5.54$, $SD = 0.99$) than with chatbots ($M = 4.56$, $SD = 1.33$). As familiarity with the medium was also moderately correlated ($r > .30$, $p < .001$) with the mediators active control and the several outcome variables, it was included as a covariate in the analyses.

RESULTS

Perceptions of origin of recommendation

We measured two additional items about perceptions of recommendation origin (human expert vs. algorithm, see Appendix C), showing no significant differences. However, as the manipulation of origin of recommendation was manipulated as an intrinsic feature of the message (O'Keefe, 2003), it may still lead to different responses – regardless of whether participants identified it as being based on human experts/ algorithms – and was included as a moderator in the second part of the analysis. For the source of communication (chatbot vs. Web site), the question wordings explicitly referred to "the chatbot" and "the Web site." Thus we did not test for whether participants perceived the recommendation as coming from a chatbot or a Web site.

Hypothesis testing

To test the hypotheses, we performed regression-based path analyses using the PROCESS macro for IBM SPSS version 25, which enabled the estimation of the conditional indirect effects in moderated mediation models (Hayes, 2017; Hayes & Matthes, 2009; Preacher et al., 2007) and test mediation and moderation simultaneously (Hayes, 2012). We used a two-step approach. In the first step, with regard to H1, H2, and RQ1, we tested the mediational effects, excluding origin of recommendation (human expert vs. algorithm). Note that anthropomorphism and social presence were not distinct on the measurement level (see Method section). Therefore, we only present results for the model including mindful anthropomorphism, as the measurement explicitly includes perceptions of human- and machine-likeness, thus directly capturing entity perceptions.[2] In the second step, with regard to H3, we included

[2] We conducted robustness checks for mindless anthropomorphism and social presence respectively, which did not significantly influence the results

origin of recommendation as a moderator. We used bootstrapping (5,000 samples) to create confidence intervals for the indirect effects of the independent variables on the dependent variables via the mediators anthropomorphism, perceived two-way communication, perceived active control, enjoyment, and perceived intrusiveness.

Parallel mediation

To test H1, H2, and RQ1, we used Model 4 and tested the effect of *source of communication* on the three outcome variables via anthropomorphism, perceived two-way communication, perceived active control, enjoyment, and perceived intrusiveness. Tables 1–4 summarize the results of the regression analyses.

Direct Effects. No direct effect of source of communication (chatbot vs. Web site) on the outcome variables recommendation adherence (b = 0.18, SE = .13, p = .171), attitudes toward the recommendation (b = −0.02, SE = .02, p = .860), attitudes toward the medium (b = −0.11, SE = .11, p = .319), and attitudes toward the organization (b = 0.07, SE = .11, p = .563) were found. The results further showed that source of communication was related to the mediators perceived two-way communication (b = −0.44, SE = .17, p = .008) and enjoyment (b = −0.70, SE = .16, p < .000). Interacting with a chatbot was perceived as higher in two-way communication and led to higher enjoyment, compared to interacting with a Web site. No significant associations were found for the mediators anthropomorphism, perceived active control, and perceived intrusiveness.

Indirect effects

Entity perceptions. Since no indirect effects of source of communication on any of the dependent variables via anthropomorphism were found, H1 cannot be supported. Anthropomorphism was not a mediator between source of communication and user responses.

Perceived interactivity. We found a significant indirect effect of source of communication on attitudes toward the medium via perceived two-way communication (95% CI = −.14, −.003). Contrary to expectations, we found a significant negative indirect effect of source of communication on attitudes toward the organization via two-way communication (95% CI = .0005, .14). No effects were found for the other outcome variables and no indirect effects were found for active control.

Experiential perceptions. We found a significant indirect effect of source of communication on recommendation adherence via enjoyment (95% CI = −.25, −.02). Furthermore, we found significant indirect effects of source of communication on attitudes toward the recommendation (95% CI = −.20, −.01), on attitudes toward the medium (95% CI = −.31, −.08), and on attitudes toward the organization (95%

CI = −.18, −.004) via enjoyment. No effects were found for perceived intrusiveness. Receiving a product recommendation from a chatbot led to more enjoyment of the interaction than receiving a product recommendation from a Web site, leading in turn to (1) higher recommendation adherence, and (2) more positive attitudes toward the recommendation, (b) the medium, and (c) the organization, partially confirming H2.

Moderated mediation

To test the moderated mediation proposed in H3, we included origin of recommendation as a moderator in the analysis, using Model 7. No significant main effects of the moderator origin of recommendation on the mediators were found. There was also no interaction effects of origin of communication and origin of recommendation.[3] In summary, with regard to H3, there was no moderated mediation.

[3] A robustness check was conducted only including participants who perceived the recommendation origin as intended (n = 139) and did not yield any significant results.

Table 1 Parallel mediation model predicting recommendation adherence

	Coefficient (SE)	p	t
Anthropomorphism	-0.05 (.39)	.777	-0.28
Perc. two-way comm.	-0.44 (.17)	.008	-2.67
Perceived active control	-0.23 (.14)	.104	-1.63
Enjoyment	-0.70 (.16)	.000	-4.35
Perceived intrusiveness	0.18 (.14)	.215	1.24
Recommendation Adherence			
Source of communication	0.18 (.13)	.171	1.37
Anthropomorphism	0.16 (.06)	.004	2.92
Perceived two-way comm.	0.06 (.07)	.447	0.76
Perceived active control	0.24 (.08)	.003	3.04
Enjoyment	0.16 (.06)	.013	2.51
Perceived intrusiveness	-0.07 (.06)	.228	-1.21
	Indirect effects		
		Confidence Interval	
	Effect (SE)	Lower limit	Upper limit
Total	-0.22 (.09)	-.41	-.04
Anthropomorphism	-0.01 (.03)	-.08	.06
Perceived two-way comm.	-0.02 (.04)	-.11	.05
Perceived active control	-0.05 (.04)	-.15	.01
Enjoyment	-0.11 (.06)	-.25	-.02
Perceived intrusiveness	-0.01 (.02)	-.05	.01

Note. $N = 242$ (.95 confidence interval). For the model predicting anthropomorphism, $F(2, 239) = 8.24.$, $p < .001$, $R^2 = .06$. For the model predicting perceived two-way communication, $F(2, 239) = 12.70$, $p < .001$, $R^2 = .10$. For the model predicting perceived active control, $F(2, 239) = 34.39$, $p < .001$, $R^2 = .22$. For the model predicting enjoyment, $F(2, 239) = 18.65$, $p < .001$, $R^2 = .14$. For the model predicting perceived intrusiveness, $F(2, 239) = 3.82$, $p < .001$, $R^2 = .03$. For the model predicting recommendation adherence, $F(7, 234) = 20.85$, $p < .001$, $R^2 = 0.38$. 5000 bootstrap samples for percentile bootstrap confidence intervals. Controlled for familiarity (medium)

Table 2 Parallel mediation model predicting attitudes towards the recommendation

	Coefficient (SE)	p	t
Attitudes recommendation			
Source of communication	-0.02 (.12)	.860	-0.18
Anthropomorphism	0.27 (.05)	.000	5.35
Perceived two-way comm.	0.06 (.07)	.403	0.84
Perceived active control	0.34 (.07)	.000	4.66
Enjoyment	0.14 (.06)	.020	2.34
Perceived intrusiveness	-0.02 (.05)	.710	-0.37
	Indirect effects		
		Confidence Interval	
	Effect (SE)	Lower limit	Upper limit
Total	-0.22 (.11)	-.43	.00
Anthropomorphism	-0.01 (.05)	-.12	.09
Perceived two-way comm.	-0.02 (.03)	-.10	.04
Perceived active control	-0.08 (.05)	-.19	.01
Enjoyment	-0.10 (.05)	-.20	-.01
Perceived intrusiveness	-0.003 (.01)	-.04	.02

Note. $N = 242$ (.95 confidence interval). For the model predicting attitudes towards the recommendation, $F(7, 234) = 39.69$, $p < .001$, $R^2 = 0.54$. 5000 bootstrap samples for percentile bootstrap confidence intervals. Controlled for familiarity (medium).

Table 3 Parallel mediation model predicting attitudes towards the medium

	Coefficient (SE)	p	t
Attitudes medium			
Source of communication	-0.11 (.11)	.319	1.00
Anthropomorphism	0.24 (.05)	.000	5.19
Perceived two-way comm.	0.14 (.06)	.022	2.31
Perceived active control	0.14 (.07)	.035	2.12
Enjoyment	0.27 (.05)	.000	4.91
Perceived intrusiveness	-0.14 (.05)	.003	-3.01
	Indirect effects		
		Confidence Interval	
	Effect (SE)	Lower limit	Upper limit
Total	-0.32 (.11)	-.54	-.10
Anthropomorphism	-0.01 (.05)	-.11	.08
Perceived two-way comm.	-0.06 (.03)	-.14	-.003
Perceived active control	-0.03 (.03)	-.11	.01
Enjoyment	-0.19 (.06)	-.31	-.08
Perceived intrusiveness	-0.03 (.02)	-.08	.01

Note. $N = 242$ (.95 confidence interval). For the model predicting attitudes towards the medium, $F(7, 234) = 56.48$, $p < .001$, $R^2 = 0.63$. 5000 bootstrap samples for percentile bootstrap confidence intervals. Controlled for familiarity (medium).

Table 4 Parallel mediation model predicting attitudes towards the organization

	Coefficient (SE)	p	t
Attitudes tow. organization			
Source of communication	0.07 (.11)	.563	0.58
Anthropomorphism	0.24 (.05)	.000	4.72
Perceived two-way comm.	-0.13 (.07)	.053	-1.94
Perceived active control	0.33 (.07)	.000	4.71
Enjoyment	0.12 (.06)	.036	2.11
Perceived intrusiveness	-0.01 (.05)	.270	-1.11
	Indirect effects		
		Confidence Interval	
	Effect (SE)	Lower limit	Upper limit
Total	-0.13 (.09)	-.30	.04
Anthropomorphism	-0.01 (.05)	-.11	.08
Perceived two-way comm.	0.06 (.04)	.0005	.14
Perceived active control	-0.07 (.05)	-.19	.01
Enjoyment	-0.09 (.04)	-.18	-.004
Perceived intrusiveness	-0.01 (.02)	-.05	.02

Note. $N = 242$ (.95 confidence interval). For the model predicting attitudes towards the organization, $F(7, 234) = 23.56$, $p < .001$, $R^2 = 0.64$. 5000 bootstrap samples for percentile bootstrap confidence intervals. Controlled for familiarity (medium).

DISCUSSION

The aim of this research was to examine the effects of interacting with a stand-alone chatbot, one of the most prominent examples of emerging AI-enabled media technologies, compared to more traditional forms of digital media such as interactive Web sites, on several affective and behavioral user responses (i.e., recommendation adherence and attitudes). To do so, we drew from the vast body of literature on interactive media effects (e.g., Sundar, 2012) and the emerging stream of research on human-machine communication (e.g., Guzman, 2019) to explicitly explore the influence on persuasive outcomes.

The first key finding is the crucial role of users' enjoyment in the persuasion context. The interaction with a stand-alone chatbot in comparison to an interactive Web site as used in this study resulted in more enjoyable user experiences, which subsequently translated into higher persuasive outcomes. This supports previous findings showing that enjoyment positively influences user attitudes in the context of electronic commerce (Hassanein & Head, 2007; M. K. O. Lee et al., 2005). Perceived intrusiveness, on the other hand, did not mediate the effects of communication source on persuasive user responses.

These findings extend human-machine communication research, seeing technology as a new entity in the communication environment (e.g., Fogg, 2002; Mou & Xu, 2017), in showing that experiential perceptions are a crucial element for users when orienting toward a chatbot as a source. In drawing this direct comparison between a Web site and a stand-alone chatbot, we find that the source characteristics of a chatbot – irrespective of the message content – influence persuasion via enjoyment as the mediating factor. We hereby extend assumptions of the MAIN model (Sundar, 2008), showing that the communication source can function as a cue that triggers the use of certain agency heuristics. Building upon these findings, this offers two important arrays for future research. First, research should further examine the specific heuristics that are important in the persuasion context. Second, there is a need to extend the comparison of different sources as done in this study and further look into the specific source characteristics that drive this effect. This implies for practitioners, extending suggestions made by previous research (Sundar et al., 2016), that using a stand-alone chatbot as a design solution for interactive message exchange can be a promising tool to create positive user engagement and enjoyable user experiences. Future research into the persuasive effects of source characteristics would help to give concrete practical design suggestions on how to design interfaces for recommendation purposes.

A second key finding concerns the attribution of humanlike characteristics to a stand-alone chatbot compared to an interactive Web site when keeping the interaction (i.e., the questions asked) constant. The fact that both were evaluated as having the same level of anthropomorphism in this study contradicts the key expectation in chatbot and robotics literature that this type of technology is perceived as more anthropomorphic (e.g., Go & Sundar, 2019). The mere presentation of a chatbot as the source of communication as done in this study was not sufficient to increase humanlikeness. This again points toward the importance of specific entity characteristics that deserve further empirical study. For example, previous research points toward linguistic elements, such as the formality of the language, including politeness or professionalism or personality cues (Nass et al., 1995, 1994), that might influence the strength of attributions of humanlike characteristics. Other elements related to modality (e.g., voice) would also be interesting given the increasing popularity of voice assistants such as Google Assistant or Amazon Alexa (e.g., Guzman, 2019).

Furthermore, our findings regarding entity perceptions point toward difficulties of distinguishing between social presence and mindful as well as mindless anthropomorphism at a measurement level. Even though conceptually different (i.e., social presence as perceiving a medium as a social entity [Xu & Lombard, 2017]; anthropomorphism as attributions of humanlike characteristics or human likeness [Kim & Sundar, 2012]), existing self-reported measurements, as used in this study, might not be sufficiently able to capture this difference, also reflected in the very high correlations among the measurements. As already suggested by previous scholars (Kim & Sundar, 2012), this could be attributed to the way the items are phrased, which makes respondents intentionally assess similarities with real human beings. More automatic social responses might not be detected with this measurement.

The third key finding is the pattern emerging for perceived interactivity. It is important to note that we did not manipulate message interactivity *per se* but compared two types of interactive media as the communication source. We did not find any effect of source of communication (chatbot vs. Web site) on persuasive outcomes via perceived active control as the mediator. One explanation could be that interactive elements in both conditions may have been sufficient for participants to feel in control of the interaction. This points toward two limitations of this study. First, the dialog with the chatbot/Web site followed a predetermined interaction flow that was used to ensure that participants in all conditions followed the same interaction pattern. Second, we adapted the interaction flow slightly for the chatbot in including self-referential statements and subtle polite elements to increase the naturalness and agency of the chatbot, which might have influenced user perceptions (Nass & Steuer, 1993; Sah &

Peng, 2015). Future research is therefore necessary to further improve the stimulus material and examine full contingencies in which all answers are based on the specific input of the participants.

The significant findings with regard to the mediating role of perceived two-way communication show, however, that a chatbot as a separate entity and possible attributions of responsiveness can contribute to interactivity perceptions as already indicated by Sundar et al. (2016). This points toward a promising line of future research regarding interactivity effects. The findings of the current study can therefore be combined with the vast body of literature with regards to perceived contingencies and message interactivity (e.g., Bellur & Sundar, 2017) in future research to distinguish between the influence of entity and message characteristics. Considering that participants might have different expectations about interactive Web sites and chatbots, this gives an interesting avenue for future research. Interestingly, the effects of perceived two-way communication on attitudes toward the medium were positive, though negative toward the recommended organization. One possible explanation is that human-chatbot interactions divert users' attention, leading them to pay more attention to the interaction itself and less to the organization (Yang & Shen, 2018). Building upon these findings, and given the importance for practitioners in choosing the type of interactive medium, the relationship between media and organizational perceptions should be investigated further in future research.

Finally, contrary to the expectations and previous findings (Senecal & Nantel, 2004; Thurman et al., 2018), the current study did not demonstrate a moderating effect of origin of recommendation (human expert vs. algorithm). This might be explained by our comparison between algorithm and human experts rather than employees or other users. Two different heuristics might have worked simultaneously. While an algorithm could have triggered a machine heuristic, leading to perceptions of objectivity, a human expert could have triggered an expertise heuristic, leading to perceptions of the expert as knowledgeable about the topic (Sundar, 2008). Future research should investigate how these specific heuristics as well as agency perceptions are related so that we can disentangle these effects.

In conclusion, this study contributes to existing literature in directly comparing stand-alone chatbots as a new communication entity with other forms of interactive media and examining the extent to which different underlying mechanisms influence user perceptions. As such, it enriches our understanding of affective and behavioral aspects of user responses to traditional and AI-based media technologies in a persuasion context.

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APPENDIX A

Table A1 Experimental conditions

Website Condition	Chatbot Condition
What is your participant ID?	Before we start: What is your participant ID?
Hello and welcome. *Expert condition:* Our experts continuously work on individual offers for our customers. Based on ten years of professional experience with customers, these experts have developed a choice model. It takes your personal details and your preferences into account. In the following you will be asked some questions that are necessary to make the best recommendation for a health insurance for you, based on this model developed by our experts *Algorithm condition:* We use algorithms to continuously work on individual offers for our customers. Based on customer data collected in the last ten years, these algorithms will calculate the best choice for you. It takes your personal details and your preferences into account. In the following you will be asked some questions that are necessary to make the best recommendation for a health insurance for you, on the basis of this algorithm.	Hello and welcome. *Expert condition:* Our experts continuously work on individual offers for our customers. Based on ten years of professional experience with customers, these experts have developed a choice model. It takes your personal details and your preferences into account. My name is Sam and I am here to assist you today. In the following I will ask you some questions that are necessary to make the best recommendation for a health insurance for you, based on this model developed by our experts *Algorithm condition:* We use algorithms to continuously work on individual offers for our customers. Based on customer data collected in the last ten years, these algorithms will calculate the best choice for you. It takes your personal details and your preferences into account. My name is Sam and I am here to assist you today. In the following I will ask you some questions that are necessary to make the best recommendation for a health insurance for you, on the basis of this algorithm. If you agree with this, please type "okay".
How old are you?	Okay, let's start. How old are you?
What is your gender?	Thanks. What is your gender?
What are the first four digits of your postcode?	Could you provide me with the first four digits of your postcode?
Are you a legal resident in the Netherlands?	Thanks. Are you a legal resident in the Netherlands?
What is the name of your current health insurance company?	Thank you for providing your demographic information. Now we move on to some other questions. Could you please tell me the name of your current health insurance company?

How important is customer service to you? Is it very important or not so important?	Okay. Now I would like to ask you some questions about your preferences. How important is customer service to you? Is it very important or not so important?
Do you travel abroad a lot?	Thanks. Do you travel abroad a lot?
We would like to get an understanding of whether you belong to a special risk group. Did you have multiple sexual partners in the last six months?	Thanks for your answer. To get an understanding of whether you belong to a special risk group, I would like to know whether you had multiple sexual partners in the last six months?
What is the budget you are willing to pay for your health insurance? Is it (1) less than 100 Euro, (2) between 100 and 300 Euro or (3) more than 300 Euro per month?	Thanks. Lastly, I would like to know the budget you are willing to pay for your health insurance. Is it (1) less than 100 Euro, (2) between 100 and 300 Euro, or (3) more than 300 Euro per month?
Expert condition: Thanks for providing your personal details and your preferences. Based on the choice model developed by our experts, we will now find the best choice for you.	*Expert condition:* Thanks for providing your personal details and your preferences. Based on the choice model developed by our experts, I will now find the best choice for you. This will take a few seconds.
Algorithm condition: Thanks for providing your personal details and your preferences. Our algorithm will now calculate the best choice for you.	*Algorithm condition:* Thanks for providing your personal details and your preferences. Our algorithm will now calculate the best choice for you. This will take a few seconds.
Expert condition: Based on the model developed by our experts, it is recommended having a look at the insurances of ZorgPlus. This company might be ideal for your demographic and fits your needs and preferences best.	*Expert condition:* Based on the model developed by our experts, I recommend having a look at the insurances of ZorgPlus. This company might be ideal for your demographic and fits your needs and preferences best.
Algorithm condition: Our algorithms have calculated the best choice for you and recommend having a look at the insurances of ZorgPlus. This company might be ideal for your demographic and fits your needs and preferences best.	*Algorithm condition:* Our algorithms have calculated the best choice for you and recommend having a look at the insurances of ZorgPlus. This company might be ideal for your demographic and fits your needs and preferences best.
Thanks for your time and goodbye! To continue, you will need a conversation code, this code is |CONVERSATIONCODE|. Please don't forget to click on submit.	Thanks for your time and goodbye! To continue, you will need a conversation code, this code is |CONVERSATIONCODE|.

APPENDIX B

Table B1 Scale items and reliability scores

Scale	Items	Cr. Alpha	M (SD)	M (SD) Chatbot	M (SD) Web-site
Mediators					
Anthropomorphism (mindful)	I perceived the chatbot/website as… Machine-like/Human-like Natural/Unnatural Artificial /Lifelike	.94	3.88 (1.41)	3.76 (1.46)	3.99 (1.36)
Anthropomorphism (mindless)	I perceived the chatbot/website as… Likable Sociable Friendly Personal	.92	4.53 (1.16)	4.49 (1.09)	4.56 (1.22)
Social Presence	While I was interacting with this chatbot/website… I felt as if it was an intelligent being. I felt as if it was a social being. I felt as if it was communicating with me. I paid attention to it. I felt involved with it. I felt as if I was alone. (reversed) I felt as if the chatbot was responding to me.	.90	4.48 (1.07)	4.54 (1.05)	4.43 (1.10)
Perceived active control	While I was using the chatbot/website, I could choose freely which information I wanted to receive. While I was using the chatbot/website, I always knew what to do next. I feel that I have a great deal of control over my experience using the chatbot/website.	.72	4.80 (1.12)	4.69 (1.10)	4.90 (1.13)
Perceived two-way communication	The chatbot/website enables conversation. The chatbot/website facilitates two-	.89	4.54 (1.24)	4.60 (1.23)	4.48 (1.25)

	way communications. It is easy to offer feedback to the chatbot/website. The chatbot/website makes me feel it wants to listen to its users.				
Enjoyment	I found the interaction with the chatbot/website... Interesting Entertaining Enjoyable Pleasant	.93	4.81 (1.23)	4.99 (1.31)	4.64 (1.13)
Perceived intrusiveness	I think the interaction with the chatbot/website was… Distracting Disturbing Forceful Interfering Intrusive Invasive Obtrusive	.93	2.89 (1.03)	2.88 (0.98)	2.90 (1.09)
Outcome variables					
Recommendation adherence	Imagine you are considering a new health insurance. Please indicate to what extent you agree or disagree with the following statements. I would purchase the recommended insurance. I don't think I would ever buy this insurance. (reversed) I would definitely follow the recommendation in the near future. It is very likely that I would buy the recommended insurance.	.81	3.83 (1.08)	3.74 (1.07)	3.91 (1.10)

Attitudes towards medium	I think the chatbot/website is… Bad/Good Unfavorable/Favorable Unsatisfactory/Satisfactory Positive/Negative Liked/Disliked	.94	4.79 (1.16)	4.73 (1.20)	4.83 (1.11)
Attitudes towards recommendation	I think the recommendation is… Bad/Good Unfavorable/Favorable Unsatisfactory/Satisfactory Positive/Negative Liked/Disliked	.95	4.66 (1.15)	4.64 (1.16)	4.68 (1.14)
Attitudes towards organization	I think the health insurance company is… Bad/Good Unfavorable/Favorable Unsatisfactory/Satisfactory Positive/Negative Liked/Disliked	.95	4.67 (1.00)	4.58 (0.97)	4.74 (1.02)
Control variables					
Familiarity (medium)	Interacting with a chatbot/website is very familiar to me. I am very knowledgeable about interacting with a chatbot/website.	.86	5.08 (1.26)	4.56 (1.33)	5.54 (0.99)
Familiarity (insurances)	Health insurances are very familiar to me. I am very knowledgeable about health insurances.	.86	5.19 (1.05)	5.18 (1.07)	5.19 (1.03)

Note. $N = 242$ ($n_{Chatbot} = 115$, $n_{Website} = 127$). All items were measured on a 7-point scale.

APPENDIX C

Table C1 Perceptions of recommendation origin

	Expert Condition		Algorithm Condition				
	M	SD	M	SD	t	df	p
Only human experts were involved in the recommendation.	3.42	1.28	3.22	1.35	1.17	240	.244
Only an algorithm was involved in the recommendation.	4.83	1.16	5.00	1.11	-1.16	240	.246

Note. $N = 242$ ($n_{Expert} = 118$, $n_{Algorithm} = 124$). Items were measured on a 7-point scale.