Don't Take it Personally: Resistance to Individually Targeted Recommendations with Anthropomorphic Recommender Systems

Guy Laban*
Institute of Neuroscience and Psychology
University of Glasgow
62 Hillhead Street
Glasgow, G12 8QB, UK
Guy.Laban@glasgow.ac.uk

Theo Araujo
Amsterdam School of Communication Research (ASCoR)
University of Amsterdam
P.O. Box 15793, 1001NG
Amsterdam, The Netherlands
T.B.Araujo@uva.nl

Abstract: Recommender agents, artificially intelligent recommender systems that demonstrate anthropomorphic cues, are widely available online to provide consumers with individually tailored recommendations. Nevertheless, little is known about the effect of their anthropomorphic cues on users' resistance to both the system and recommendations. Moreover, individually tailored recommendations require users to disclose information proactively or reactively for receiving customized or personalized recommendations, which can trigger users' resistance to the platform and the recommendations. Accordingly, this study examined the extent to which recommender systems' anthropomorphic cues and the type of recommendations provided (customized and personalized) influenced online users' perceptions of control, trustworthiness, and the risk of using the platform. The study assessed how these perceptions, in turn, influence users' adherence to the recommendations. An online experiment among online users ($N = 266$) with recommender agents and web recommender platforms that provided customized or personalized restaurant recommendations was conducted. The results of the experiment entail that when recommendations are customized, as compared to personalized, users are less likely to demonstrate resistance and are more likely to adhere to the recommendations provided. Furthermore, the study's findings suggest that these effects are amplified for recommender agents, demonstrating anthropomorphic cues, in contrast to traditional systems as web recommender platforms.

Keywords: recommender systems, conversational agents, chatbots, recommender agents, human-agent interaction, personalization, customization, online marketing

Introduction

Recommender systems, computer software that provides users with suggestions for supporting decision-making processes (Ricci, Rokach, & Shapira, 2011), often use one-to-one marketing techniques (Peppers & Rogers, 1997; Peppers, Rogers & Dorf, 1999; Shaffer & Zhang, 2002). These marketing procedures aim to target and tailor suggestions for individuals (Salonen & Karjaluo, 2016). As these have become more common online, artificial entities

such as conversational agents, artificially intelligent computer programs that interact with users by using natural language (Atwell & Shawar, 2007; Griol, Carbó, & Molina, 2013), are being integrated as recommender agents (Christakopoulou, Radlinski, & Hofmann, 2016; Daniel, Zaccaria, Matera, & Dell'Orto, 2018; Qiu & Benbasat, 2009). These are already applied by marketers to provide consumers with individually tailored experiences; this is done by targeting individual needs and communicating in a flowing dialogue, potentially increasing consumer engagement (see Kojouharov, 2018; Modgil, 2018). Designed with cognitive architectures to communicate in a human-like way (Eyssel, Kuchenbrandt, & Bobinger, 2011; Eyssel, Kuchenbrandt, Bobinger, de Ruiter, & Hegel, 2012), these conversational agents are often described and perceived as anthropomorphic and are evaluated in a human-like way (Araujo, 2018).

In an industry study by Forrester Consulting (2019) with enterprise directors, 73% of the participants reported that their organization is adopting self-service channels, and 68% of the participants reported to use chatbots to give real-time answers to their customers. Predictions entail that chatbots will save businesses about \$8 billion per year by 2022, with adapting business potentially increasing growth by an average of 30% annually (Deloitte, 2019). Organizations in the domains of healthcare and banking using chatbots could see timesaving of over four minutes per enquiry which is equivalent to \$0.50-\$0.70 per interaction (Forrester, 2019).

Undoubtedly, marketers find this technology to be beneficial with over 100,000 active messenger agents on Facebook by April 2017, in oppose to only 33,000 six months before it (Facebook IQ, 2018), and with nearly 67% of millennials from the United States (US) reporting that they are likely to purchase products directly from conversational agents (McCarthy, 2017).

Moreover, a report by Deloitte (2019) describes that there seems to be a general agreement across experts in the field, with 67% of industry professionals reporting to believe that chatbots will outperform mobile apps in the settings of e-commerce in the upcoming 5 years. Therefore, with 2 billion users using mobile messaging apps by 2018 (about 80% of all smartphone users), we should expect to see substantial growth in customer adaption (Deloitte, 2019). While conversational and recommender agents are embraced in the industry, it is still unclear how users perceive these, how their anthropomorphic cues influence these perceptions and the corresponding recommendations.

Individually tailored recommendations are often either customized or personalized. Customized recommendations are user-initiated, with users proactively disclosing relevant information. Alternatively, personalized recommendations are system-initiated, based on previously collected consumer data such as online behavior and personal information (Arora et al., 2008; Kalyanaraman & Sundar, 2006; Sundar & Marathe, 2010; Sundar, 2020; Sun, May, & Andrew, 2016). As such, these techniques often require users to either proactively or reactively disclose private information (Sundar, 2020; Zhang & Sundar, 2019). The act of self-disclosure, being a key factor for building relationships (Jourard & Lasakow, 1958; Pearce & Sharp, 1973), can facilitate relationships and improve bonding. Nonetheless, when the disclosure is forced it can feel invasive, unnatural, uncomfortable, or unethical (Altman & Taylor, 1973; Derlega, Harris, & Chaikin, 1973). Accordingly, tailored marketing can have positive persuasive implications (Salonen & Karjaluo, 2016), but the necessity of disclosing information (Chellappa & Sin, 2005; Kaptein, Markopoulos, de Ruyter, & Aarts, 2015) can also trigger resistance among users (e.g., Baek & Morimoto, 2012; Wang, Zheng, Jiang, & Ren, 2018).

The persuasive implications of anthropomorphic agents in marketing setting are widely addressed in the literature (e.g., Delbaere, McQuarrie, & Phillips 2011; Hart & Royne, 2017; Kim & McGill, 2011; Laksmidewi, Susianto, & Afif, 2017), yet, there is a knowledge gap regarding the consequences of anthropomorphic recommender agents. While previous studies explain that people don't differ in their disclosures to artificial agents based on their anthropomorphic cues of embodiment (Laban, George, Morrison, & Cross, 2020; Laban, Morrison, & Cross, 2020), it is unclear if anthropomorphic embodiment will affect people's perceptions in e-commerce settings, and when disclosure is reactive or proactive. Considering the persuasive implications of recommender systems and one-to-one marketing techniques (Chellappa & Sin, 2005; Kaptein et al., 2015; Salonen & Karjaluo, 2016), there is a need to further explore how recommender agents' anthropomorphic cues disrupt these procedures. The potential contribution of anthropomorphic cues to the recommender system experience should be further explored to understand how these affect users' resistance to the system and recommendations provided.

Through an online experimental design with recommender agents and web recommender platforms that provided customized or personalized restaurant recommendations, two main aims were addressed. First, this study aimed to reduce the knowledge gap regarding the implications of recommender systems' anthropomorphic cues on user resistance to both the systems and recommendations. Moreover, the study aimed to expand the theoretical scope of proactive and reactive information disclosure in online marketing settings and to evaluate the influences anthropomorphic cues have on these procedures. Hence, the following research question is proposed

RQ: To what extent do recommender systems' anthropomorphic cues and the type of recommendations provided affect online users' adherence to recommendations?

Theoretical Framework

Persuasive Resistance

Users can avoid recommendations and resist the persuasive nature of both recommendation systems and one-to-one marketing solutions for various reasons (Peppers & Rogers, 1997; Peppers et al., 1999; Ricci et al., 2011; Shaffer & Zhang, 2002). The persuasion resistance model (Fransen, Smit, & Verlegh, 2015) explains that a primary motivation for resisting a message is a threat to freedom. People might feel that their freedoms are being threatened when their sense of autonomy and independence is disrupted (Brehm & Brehm, 1981). Another important motive for persuasive resistance is a reluctance to change (Fransen et al., 2015), especially when an individual feels they have lost control or are being threatened (Conner, 1992). Concern of deception is the last motive in persuasion resistance (Fransen et al., 2015), as people desire accurate information and do not want to be fooled (Chaiken, 1980; Petty & Cacioppo, 1979; Petty, Tormala, & Rucker, 2004). When an individual perceives a message as untrustworthy, deceiving, risky, or limiting, their defense mechanisms react with resistance accordingly (Jain & Posavac, 2004).

Trust, risk, and control have traditionally been vital factors for organizations to adopt innovative online solutions and a basis for consumer evaluation (de Ruyter, Wetzels, & Kleijnen, 2001; Featherman & Pavlou, 2003; Gefen & Straub, 2004). Cofta (2007) describes the three as necessary channels for feeling certainty, confidence, and autonomy. Gerck (2002) specifically addressed these in relation to information systems. It is therefore expected that when an

individual is evaluating a recommender system, trust in the platform, perceived risk, and perceptions of control will influence the sense of resistance towards the system.

Anthropomorphic Cues

How recommendations are communicated can influence how users evaluate them (Ricci et al., 2011). Recommender agents differ in their communication methods from traditional recommender systems and are anthropomorphized to communicate recommendations in a human-like way (Daniel et al., 2018). Anthropomorphism is described as the attribution of human characteristics to non-human entities (Nass & Moon, 2000). The extent to which an agent can exhibit and imitate human characteristics is simulated by its anthropomorphic cues; these are visual or behavioral cues that resemble human characteristics and trigger anthropomorphic perceptions of the agent (de Visser et al., 2016). Communicating recommendations through a dialogue and natural language, while sustaining a human-like identity (i.e., having a human name and talking in first-person singular pronouns), constitutes potential anthropomorphic cues that can prime an individual's perception of recommender agents (Araujo, 2018; Daniel et al., 2018; Laban & Araujo, 2020). Furthermore, users' perceptions of agents are driven by their cognitive reconstruction, wherein their beliefs or expectations about an agent further shape perception and behavior (Cross, Ramsey, Liepelt, Prinz, Hamilton, 2016). Hence, perceptions of anthropomorphism are not merely dependent on visual cues but can be driven by the agent's behavioral cues (e.g., figure of speech), or previous expectations and perceptions of the agent.

Theory of mind (Premack & Woodruff, 1978) is a fundamental framework for understanding the cognitive and social effects of anthropomorphic cues. This refers to the human ability to attribute mental states to oneself and others, understanding that others might have beliefs, opinions, emotions, or perspectives that differ from one's own (Premack & Woodruff,

1978). Accordingly, the theory of mind perception explains that people can ascribe mental capacities to other entities—human and nonhuman—and then react to and evaluate these based on their moral judgments and values (Epley & Waytz, 2010; Gray, Young, & Waytz, 2012; Waytz, Cacioppo, Epley, 2010; Wegner, 2002). Previous studies support these propositions, reporting that people respond to conversational agents' anthropomorphic cues in a social way; they attribute intentions and feelings to the agents (Holtgraves, Ross, Weywadt, & Han, 2007), and perceive them as more trustworthy than non-anthropomorphic systems (Cassell & Bickmore, 2000; de Visser et al., 2016). A previous study entails that when chatbot's actions were perceived to comply with positive moral intentions, i.e., being more cooperative, it was perceived as more anthropomorphic and to be providing a better quality of information. Accordingly, it was evaluated more positively in terms of service performance (Laban & Araujo, 2020). Moreover, anthropomorphic cues were found to positively affect consumers' purchase intentions, attitudes, and brand liking when used for branding products (Delbaere et al., 2011; Hart & Royne, 2017; Laksmidewi et al., 2017).

Consequently, in line with mind processing theory (Epley & Waytz, 2010; Gray et al., 2012; Waytz et al., 2010; Wegner, 2002) it is proposed that users should ascribe mental capacities to recommender agents (i.e., recommender systems with anthropomorphic cues), and evaluate these based on their moral judgments and values. Users do not ascribe mental capacities to traditional recommender systems, as these do not demonstrate anthropomorphic cues. Therefore, when using recommender agents, compared to web recommender platforms, users are more likely to adhere to recommendations and to perceive more control, less risk, and that the platform is more trustworthy. As different tailoring techniques have different persuasive

consequences (Chellappa & Sin, 2005; Kaptein et al., 2015), this is expected to be conditional based on the type of recommendations provided.

Users tend to positively evaluate customized recommendations as they are user-initiated and based on proactively disclosed information (Arora et al., 2008; Kalyanaraman & Sundar, 2006; Sundar & Marathe, 2010). Several studies have reported that users find customized recommendations to be satisfying (Kalyanaraman & Sundar, 2006; Sundar & Marathe, 2010; Sun et al., 2016) and ethical (Treiblmaier, Madlberger, Knotzer, & Pollach, 2004). Furthermore, Daniel et al. (2018) demonstrated that users had positive reactions to customized recommendations when provided by conversational agents. Hence, it is expected that the effect of a recommender system's anthropomorphic cues is conditional on its customized recommendation, with the following hypothesis proposed

H₁: Receiving customized recommendations from a recommender agent, compared to a web recommender platform, will have a positive effect on users' perceptions of (a) control, (b) the platform's trustworthiness, (c) being less risky, and on (d) adherence to recommendations.

Disclosure as a Voluntary Process

One-to-one marketing techniques rely on getting to know user traits in order to tailor individual marketing solutions and recommendations (Peppers & Rogers, 1997; Peppers et al., 1999; Shaffer & Zhang, 2002). As these are based on users' information, these techniques often require users to proactively or reactively disclose private information. Accordingly, the persuasive consequences of these recommendations are highly dependent on the tailoring method, customization or personalization, and the essence of disclosure associated with it (Chellappa & Sin, 2005; Kaptein et al., 2015).

Self-disclosure is a communication behaviour aimed at introducing and exposing oneself to others, and is a key factor for building relationships between two entities (Jourard & Lasakow, 1958; Pearce & Sharp, 1973). Self-disclosure can be perceived as a complicated and dynamic social process that can facilitate relationships and improve bonding. However, when the procedure is involuntary or unnatural it could be perceived as invasive, abnormal, uncomfortable, or unethical (Altman & Taylor, 1973; Derlega et al., 1973). When the level of disclosure does not correspond with expectations, it can damage the relationship (Archer & Berg, 1978; Derlega, et al., 1973).

Since personalized recommendations are system-initiated, based on previously collected consumer data such as online behaviour and personal information (Arora et al., 2008; Kalyanaraman & Sundar, 2006; Sundar & Marathe, 2010), disclosure can feel forced, unnatural, invasive, and involuntarily (Chellappa & Sin, 2005; Wang et al., 2018). Previous studies reported that personalized content and recommendations can affect a user's sense of vulnerability; users feel that their privacy is violated, that they are losing control over their private information, and that the platform is risky (e.g., Baek & Morimoto, 2012; Chellappa & Sin, 2005; Puzakova, Rocereto, & Kwak, 2013; Wang et al., 2018). This can manifest as lower adaptation rates (Chellappa & Sin, 2005; Chen, Feng, Liu, & Tian, 2019; Wang et al., 2018), increasing skepticism towards the recommendation and the source (Chen et al., 2019), and an increasing likelihood of avoidance (Baek & Morimoto, 2012).

As users ascribe mental capacities to recommender systems that are anthropomorphized (i.e., recommender agents) and evaluate these accordingly (Epley & Waytz, 2010; Gray et al., 2012; Waytz et al., 2010; Wegner, 2002), it is expected that when the disclosure feels forced, one will experience a greater sense of resistance towards the recommender agent. On the contrary,

users are less likely to ascribe moral meaning to recommender systems that lack anthropomorphic cues (Epley & Waytz, 2010; Gray et al., 2012; Waytz et al., 2010; Wegner, 2002), and are thus less likely to demonstrate a sense of resistance to personalized recommendations. Hence, it is expected that the users' sense of resistance to personalized recommendations from web recommender platforms will be lower than when receiving personalized recommendations from a recommender agent. Following, the second hypothesis is proposed

H₂: Receiving personalized recommendations from a recommender agent, as compared to a web recommender platform, will have a negative effect on users' perceptions of (a) control, (c) the platform's trustworthiness, (c) being less risky, and on (d) adherence to recommendations.

Moreover, since self-disclosure is at the core of interpersonal relations (Altman & Taylor, 1973; Jourard & Lasakow, 1958; Pearce & Sharp, 1973), the persuasive consequences of one-to-one marketing (Chellappa & Sin, 2005; Kaptein et al., 2015) are likely heightened when morally evaluated following the recommender system's anthropomorphic cues (Epley & Waytz, 2010; Gray et al., 2012; Waytz et al., 2010; Wegner, 2002). Accordingly, recommender agents providing personalized recommendations will be perceived more negatively than those providing customized recommendations. Hence, the following hypothesis is proposed

H₃: Recommender agents that provide personalized recommendations, as compared to customized recommendations, will have a negative effect on users' perceptions of (a) control, (b) the platform's trustworthiness, (c) being less risky, and on (d) adherence to recommendations.

Disclosure as an Exchange

The act of self-disclosure with a platform resembles a procedure of social exchange (Joinson, Reips, Buchanan, & Paine Schofield, 2010). Social exchange theory (Homans, 1961) states that relationships are formed through the interplay of cost and reward, while comparing alternatives. With self-interest and interdependence as the basic features of an interaction, two entities hold a certain value and develop a relationship following the exchange of value. For subjective self-interests (i.e., economic, social, or psychological needs), exchange is perceived as a social behavior with a potential economic or social outcome (Ekeh, 1974; Homans, 1961; Lambe, Wittmann, & Spekman, 2001; Lawler, 2001; Lawler & Thye, 1999). Social exchange has been extended beyond interpersonal relationships to explain the development and formation of relationships in various settings, including business-oriented and marketing relationships (see Lambe et al., 2001; Lawler & Thye, 1999).

When users self-disclose to online platforms (e.g., recommender systems), they share requested information for authentication or marketing purposes (Joinson et al., 2010). Furthermore, according to the privacy paradox, people tend to disclose private information despite their privacy-oriented views, attitudes, and preferences (Barnes, 2006; Debatin, Lovejoy, Horn, & Hughes, 2009), while treating disclosure as a potential tradeoff (Barth & de Jong, 2017; King, 2015; Utz & Krämer, 2009). This tradeoff acts as a social exchange; the disclosure is treated as a cost, perceived as a worthy exchange for social or economic rewards (King, 2015). On social media, for example, people tend to disclose private information for impression management (Utz & Krämer, 2009), and they are willing to disclose private information for monetary rewards (Carrascal, Riederer, Erramilli, Cherubini, & de Oliveira, 2013; Huberman, Adar, & Fine, 2005), convenience, promotions, and discounts (Beresford, Kübler, & Preibusch, 2012; Hann, Hui, Lee, & Png, 2007).

Thus, since users do not ascribe any mental capacities to recommender systems' without anthropomorphic cues (Epley & Waytz, 2010; Gray et al., 2012; Waytz et al., 2010; Wegner, 2002), their evaluations of the platform and recommendations will be determined through the social exchange of cost and reward (Ekeh, 1974; Homans, 1961; Joinson et al., 2010; Lambe et al., 2001; Lawler, 2001; Lawler & Thye, 1999). Following the privacy paradox (Barnes, 2006; King, 2015), it is suggested that when using web recommender platforms, the reward of receiving an individually targeted recommendation (Salonen & Karjaluo, 2016) can overcome the triggered resistance to the tailoring technique (Chellappa & Sin, 2005; Kaptein et al., 2015). Accordingly, it is expected that users perceive and evaluate web recommender platforms that provide personalized recommendations similarly to those that provide customized recommendations. Hence, the following hypothesis is proposed

H₄: There are no differences between web recommender platforms that provide customized and personalized recommendations regarding users' perceptions of (a) control, (b) the platform's trustworthiness, (c) risk, and (d) adherence to recommendations.

Psychological Reactance

Psychological reactance is a motivational reaction to a situation, resulting with people rejecting, ignoring, or avoiding entities they perceive as threatening and limiting to their behavioral freedoms (Brehm & Brehm, 1981). In line with the persuasion resistance model (Fransen et al., 2015), it is expected that when users experience a greater sense of resistance, this will be reflected in their adherence to the recommendations provided. Further, users' perceptions of the platforms' trustworthiness, risk, and level of control when using the platform should also be reflected in the users' adherence to the provided recommendations, by either following or

avoiding them. Accordingly, the recommender systems' anthropomorphic cues and the type of recommendations provided are also expected to have an indirect effect on users' adherence to the recommendations by triggering psychological reactance (Brehm & Brehm, 1981). These are expected to be mediated through the user's trust in the platform, perceived risk, and perceived control when using the platform. Hence, the last hypotheses are suggested

H₅: Receiving customized recommendations from a recommender agent, as compared to a web recommender platform, will have a positive indirect effect on users' adherence to recommendations, mediated through users' (a) perceived control, (b) perceived trustworthiness, and (c) perceived risk.

H₆: Receiving personalized recommendations from a recommender agent, as compared to a web recommender platform, will have a negative indirect effect on users' adherence to recommendations, mediated through users' (a) perceived control, (b) perceived trustworthiness, and (c) perceived risk.

H₇: Recommender agents that provide personalized recommendations, as compared to customized recommendations, will have a negative indirect effect on users' adherence to recommendations, mediated through users' (a) perceived control, (b) trust in the perceived trustworthiness, and (c) perceived risk.

See Figure 1 for the conceptual model.

Figure 1. Conceptual model.

Methods

Design and Procedure

A two (anthropomorphic cues: recommender agent vs. web recommender platform) by two (type of recommendations: customization vs. personalization) between-subjects factors online experiment was conducted. Participants were informed regarding their rights and were asked to provide their informed consent; participants who consented then began the experiment. First, participants answered a set of demographic questions and an attention check. Then, they were randomly assigned to one of the four groups and received corresponding instructions. Using either a recommender agent or a web recommender platform, participants answered three open-ended questions—disclosing a favourite cuisine, their budget for a meal, and preferable location for a restaurant. Accordingly, the recommender system provided either customized or personalized recommendations. When receiving customized recommendations, the platform explained that the recommendations were based on the participant's answers, whereas when receiving personalized recommendations, the platform explained that the recommendations were based on the participant's online behavior and social media information. Participants were informed that the manipulation should not take more than three minutes.

After completing the task, participants evaluated the platform, the recommendations, and self-reported their affinity with technology and need for cognition. Once participants completed the experiment, they were debriefed about the study and provided with researcher contact information. The study received an ethics review board approval.

Participants

A priori sample size computation using the software G*Power version 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009; Faul, Erdfelder, Lang, & Buchner, 2007) indicated that for finding a medium effect size ($R^2=0.09$) with 95% confidence intervals, the required sample size is at least 180 units. A total of 300 participants were recruited using Amazon Mechanical Turk (MTurk). The sample consisted of English-speaking people between the ages of 19 to 65, who reside in the US, and reported using a mobile or desktop instant messaging application.

Out of 300 participants, 13 were dropped because of technical issues and another six for failing the attention checks. An outliers check was conducted using values of Mahalanobis distance, Cook's D, and Leverage, controlling for participant's manipulations' perceived realism. Units that were considered outliers by at least two of the distance or leverage values were individually examined, resulting in 15 dropped cases. Thus, the final sample size consisted of 266 total participants between the ages of 19 to 65 ($M = 38.33$, $SD = 12.20$), with 42.1% females, and most having completed a bachelor's degree (51.5%) or secondary school/high school (32.7%).

Stimuli

Anthropomorphic cues. The independent variable “anthropomorphic cues” concerned the systems’ demonstration of human-like communication through the manipulation of language, dialogue, symbols, and icons (Daniel et al., 2018; de Visser et al., 2016). For the scope of the study, the anthropomorphic cues of a recommender system were manipulated by employing a recommender agent; a conversational agent with a human name (“Emma”) that spoke using first-person singular pronouns. Emma communicated with the participants via online chat and described recommendations with nouns and adjectives (e.g., “These restaurants should provide a lavish experience!” when describing expensive restaurants). Emma also used greetings (e.g., “Hi”) and reacted to

Figure 2. Recommender agent providing customized recommendations.

Restaurant Recommendations

Answer the following questions to receive a restaurant recommendation

Indicate the type of food you would like to eat:

Indicate your budget for a meal:

Indicate in which city you would like to eat:

Figure 3. Web recommender platform providing customized recommendations.

users' statements (e.g., "My pleasure!") (see Figures 2 and 4). The agents were created using the Conversational Agent Research Toolkit (Araujo, 2020).

A recommender system that lacked anthropomorphic cues was manipulated by using a traditional recommender system (i.e., a web recommender platform). The platform utilized buttons, icons, and windows (e.g., a "Go" button to submit values and a pop-up window to show recommendations), to stimulate the impression of a standard website (Sundar & Marathe, 2010). Recommendations were described with a passive voice and common symbols and icons (e.g., "\$" for describing budget) (see Figures 3 and 5).

Restaurant Recommendations

Receive a restaurant recommendation following your online behaviour

Indicate the type of food you would like to eat:

Indicate your budget for a meal:

Indicate in which city you would like to eat:

Figure 5. Web recommender platform providing personalized recommendations.

Figure 4. Recommender agent providing personalized recommendations.

Type of Recommendations. The independent variable “type of recommendation” is concerned with the tailoring technique employed to generate a recommendation. The concept includes two types of recommendations following Sundar’s and Marathe’s definitions (2010)—customized and personalized. Customized recommendations are user-initiated and the result of the user’s conscious proactive information disclosure. Personalized recommendations are system-initiated and based on the user’s reactive disclosure of online behaviour and social media information. While participants in both conditions went through the same procedure, they were explicitly informed that the recommendations they received were either based on their answers (i.e., customized; see Figures 2 and 3) or on their online behaviour and social media information (i.e., personalized; see Figures 4 and 5).

Measurements

Principal axis factoring (PAF) analysis was conducted with 51 items that measure the concepts ‘perceived anthropomorphism’ (5 items), ‘perceived control’ (6 items), ‘trustworthiness’ (6 items), ‘perceived risk’ (8 items), ‘affinity with technology’ (9 items) and ‘need for cognition’ (17 items). After inspecting the correlation matrix, it is noticeable that there is no threat of multicollinearity and that there are no threats to the variables’ discriminant validity, as none of the correlations is above .85 (highest correlation is .71). Moreover, the Kaiser-Meyer-Olkin measure of sampling adequacy was .89, above the recommended value of .6, and Bartlett’s test of sphericity was significant, $\chi^2(1275) = 10077.18, p < .001$. The diagonals of the anti-image correlation matrix were all over .5, supporting the inclusion of each item in the analysis.

Eight components were found with an eigenvalue above 1 according to the eigenvalue-criterion. Together, these components explain 68.23% of the variance in the original items.

According to the results of an oblique rotation, the items were divided between the components, which can be labelled as (1) 'need for cognition (looking for cognition)', (2) 'perceived risk', (3) 'perceived anthropomorphism', (4) 'locus of causality', (5) 'internal controllability', (6) 'need for cognition (avoiding cognition)', (7) 'affinity for technology', and (8) 'trustworthiness'.

Manipulation checks.

Perceived anthropomorphism. The anthropomorphic cues manipulation was assessed using an adapted scale from Bartneck, Kulic', Croft, and Zoghbi (2009) and Powers and Kiesler (2006). This consisted of five items evaluated on a seven-point semantic bipolar scale. These items represent the possible identification differences between a human and a machine, where a higher score indicates humanlike agent behavior, and a lower score represents a mechanical behavior that is associated with robots and machines (Bartneck et al., 2009). The scale was reliable ($\alpha = .94$, $M = 4.12$) and a mean index was created accordingly.

Attribution of the recommendations to a source. The type of recommendations manipulation was assessed using a manifest dichotomous item. This asked participants to attribute the recommendations they received to either their own answers or their online behavior and social media information.

Mediators.

Perceived control. Perceived control refers to ones' internal attribution of control during the procedure. The concept was measured using the locus of causality and internal controllability indicators from the Causal Dimension Scale (Russel, 1982), based on Weiner's model of attribution (1979). Both scales include three bipolar items with semantic differences on a seven-point range that were adjusted to fit the context of the current study and experimental treatment,

rather than to general events. The scale was reliable ($\alpha=.82$, $M=3.86$) and a mean index was created accordingly.

Trustworthiness. Trustworthiness refers to the extent of the participant's self-assessed state of trust in the platform after exposure to the treatment (Chang, Wong, & Lee, 2015). Following Chang et al. (2015), trustworthiness in the context of information systems includes two indicators, general trust in the platform and trust regarding privacy. General trust in the platform was measured using three Likert-scale statements on a seven-point range, adapted from Wu, Huang, Yen, and Popova (2012). Trust regarding privacy was measured using three more Likert-scale statements, also on a seven-point range, adapted from Dinev, Xu, Smith, and Hart (2013). The items were adjusted to fit the context of the current study and referred to the experimental treatment rather than general events. The scale was reliable ($\alpha = .91$, $M = 4.52$) and a mean index was created accordingly.

Perceived risk. When a situation or a process creates a sense of concern, discomfort, and/or anxiety, this is known as perceived risk (Dowling & Staelin, 1994). Following Chang et al. (2015), perceived risk in the context of information systems includes two indicators, general risk and privacy concerns. General risk was measured using four Likert-scale statements on a seven-point range adapted from Chang et al. (2015), Dinev and Hart (2006) and Malhotra, Kim, and Agarwal (2004). Privacy concerns were measured using four Likert-scale statements on a seven-point range adapted from Chang et al. (2015), Dinev and Hart (2006) and Dinev et al. (2013). The items were adjusted to fit the context of the current study and referred to the experimental treatment rather than general events. The scale was reliable ($\alpha = .94$, $M = 3.79$) and

a mean index was created accordingly.

Dependent variable.

Adherence to recommendations. The concept addresses the participant's likelihood to

Table 1. Summary Statistics of the Variables

	Mean	SD	α	min	max
Perceived Anthropomorphism	4.12	1.73	0.94	1	7
Perceived Control	3.86	1.27	0.82	1	7
Trustworthiness	4.52	1.30	0.91	1	7
Perceived Risk	3.79	1.47	0.94	1	7
Adherence to Recommendations	4.94	1.73	-	1	7
Affinity with Technology	3.91	0.72	0.90	1	5
Need for Cognition	3.44	0.80	0.93	1	5
Age	38.33	12.20	-	19	65
Perceived Realism	5.01	1.79	-	1	7
<i>N</i>	266				

follow or avoid the recommendations provided by the recommender system. As a manifest concept, participants were asked to rate their likelihood to follow or avoid the recommendations provided on a seven-point scale.

Control variables.

Affinity for technology. Affinity for technology controls for participant's familiarity and personal affection towards technology (Edison & Geissler, 2003). This concept was measured using nine items with five-point Likert-scales, adapted from Edison and Geissler (2003). The scale was reliable ($\alpha = .90$, $M = 3.91$) and a mean index was created accordingly.

Need for cognition. Need for cognition refers to the degree to which an individual is willing to engage with and would enjoy a cohesive information processing task (Cacioppo, Petty, & Kao, 1984). This concept was measured using 17 items with five-point Likert-scales, adapted

from Cacioppo et al. (1984). The scale was reliable ($\alpha = .93$, $M = 3.44$) and a mean index was created accordingly.

Demographics. The questionnaire included the demographic items age, biological sex, country of residence, country of origin, and the highest level of completed education.

Manipulations' perceived realism. To control for the objectivity of the manipulation in the manipulation checks and outlier inspection, participants were asked to evaluate how realistic they found the manipulations to be, on a seven-point Likert-scale.

Results

Pretest

A pretest was conducted with a two (anthropomorphic cues: recommender agent vs. web recommender platform) by two (type of recommendations: customization vs. personalization) between-subjects factors online experiment. A total of 150 participants between the ages of 19 and 57 ($M = 32$, $SD = 8.02$) were recruited using MTurk, of which 46.3% were females, and most have completed a bachelor's degree (56.8%) or secondary school/high school (24.9%). Participants were randomly assigned to one of the four groups, and after completing the manipulation task, participants answered a questionnaire evaluating the platform's anthropomorphic cues and indicating the source of information upon which the recommendations were based.

Independent-samples t-test indicated that recommender agents ($M = 4.71$, $SD = 1.56$) were perceived as more anthropomorphic than web recommender platforms ($M = 3.53$, $SD = 1.69$), $t(148) = -5.90$, $p < .001$, 95% CI [1.57, -.78], $d = .72$. A chi-square test demonstrated that personalized recommendations are associated with participants' attributing the recommendations

to their online behaviour, $\chi^2(1) = 75.12$, $\Phi = -.53$, $p < .001$. Hence, both conditions were successfully manipulated in the pretest.

Manipulation checks

A one-way ANCOVA indicated that recommender agents ($M = 4.51$, $SE = .11$, 95% CI [4.29,4.73]) were perceived as more anthropomorphic than web recommender platforms ($M = 3.73$, $SE = .11$, 95% CI [3.51,3.95]), $F(1,263) = 24.06$, $p < .001$, controlling for the manipulations' perceived realism. A binary logistic regression indicated that participants are significantly less likely to attribute customized recommendations, compared to personalized, to their online behaviour than to their answers, $b = -2.75$, $p < .001$, $OR = .06$, 95% CI [.03,.13], holding the manipulations' perceived realism constant. Therefore, both conditions were successfully manipulated.

Randomization

To test whether the sample data was distributed equally across conditions randomization checks were performed. A one-way ANOVA was performed for age, $F(3, 265) = .20$, $p = .894$. Chi-square tests were used to check both the level of education, $\chi^2(12) = 6.64$, $p = .880$, and gender, $\chi^2(3) = 7.01$, $p = .072$. It can therefore be concluded that there were no issues with the distribution of the sample data.

Hypotheses testing

A moderated mediation analysis was conducted using Model 8 of PROCESS Macro 3.2 to SPSS (Hayes, 2018a) to explain the outcome of adherence to recommendations based on the platforms' anthropomorphic cues and the type of recommendations as independent variables and moderators; perceived control, trustworthiness, and perceived risk as mediators; and age, gender,

level of education, affiliation with technology, and need for cognition as covariates (see Figure 6).

Figure 6. Statistical model (see Hayes, 2018a; 2015; 2018b).

Table 2. Unconditional effects

	Adherence to Recommendations	Perceived Control	Trustworthiness	Perceived Risk
Anthropomorphic cues	0.82** [0.33,1.31]	0.49* [0.07,0.91]	0.05 [-0.39,0.48]	-0.25 [-0.73,0.23]
Types of recommendations	-0.03 [-0.54,0.47]	-0.05 [-0.48,0.39]	-0.51* [-0.95,-0.06]	0.62* [0.13,1.11]
Interaction term	-0.73* [-1.44,-0.03]	-0.62* [-1.23,-0.01]	-0.02 [-0.65,0.60]	0.51 [-0.17,1.20]
Perceived control	0.37*** [0.22,0.51]	-	-	-
Trustworthiness	0.64*** [0.47,0.82]	-	-	-
Perceived risk	-0.22** [-0.38,-0.05]	-	-	-
Need for cognition	0.14 [-0.11,0.39]	0.19 [-0.03,0.40]	-0.06 [-0.28,0.16]	-0.25* [-0.49,-0.01]

Affinity for technology	0.08 [-0.20,0.36]	-0.16 [-0.40,0.07]	0.25* [0.00,0.49]	0.07 [-0.20,0.34]
Gender	0.32 [-0.04,0.67]	0.29 [-0.01,0.60]	0.11 [-0.21,0.43]	-0.03 [-0.38,0.32]
Age	-0.01 [-0.03,0.00]	0.01 [-0.00,0.02]	-0.01 [-0.02,0.00]	-0.00 [-0.02,0.01]
Level of education	-0.13 [-0.38,0.11]	-0.18 [-0.39,0.03]	0.03 [-0.19,0.25]	0.26* [0.02,0.50]
R^2	0.37	0.09	0.07	0.13
F	13.33	3.13	2.58	4.75
N	266	266	266	266

95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Interaction term - Anthropomorphic cues * Types of recommendations

Perceived Control

Table 3. Conditional direct effects

		Perceived control		
		<i>b</i>	<i>t</i>	95% CI
Anthropomorphic cues	Customized	0.49* (0.21)	2.29	0.07, 0.91
	Personalized	-0.13 (0.22)	-0.58	-0.56, 0.31
Type of recommendations	Recommender Agent	-0.67* (0.22)	-3.09	-1.09, -0.24
	Web Recommender Platform	-0.05 (0.22)	-0.21	-0.48, 0.39

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The model explaining perceived control was significant, $R = .30$, $F(8, 257) = 3.13$, $p = .002$, with 8.9% ($R^2 = .089$) of the variance in perceived control explained. The main effect of the platforms' anthropomorphic cues was significant, $b = .49$, $t(257) = 2.29$, $p = .023$. The main effect of the type of recommendations, however, was not. The unconditional interaction effect of the platforms' anthropomorphic cues and the type of recommendations was significant, $b = -.62$, $t(257) = -2.01$, $\Delta R^2 = .01$, $\Delta F(1, 257) = 4.05$, $p = .045$ (see table 2).

A test for conditional effects revealed that recommender agents had a significant positive effect on perceived control, for customized recommendations, $b = .49$, $t(257) = 2.29$, $p = .023$, 95% CI [.07, .91], while the effect is insignificant for personalized recommendations. Hence, H_{1a} is supported and H_{2a} is rejected. The test also found that customized recommendations had a significant positive effect on perceived control for recommender agents, $b = -.67$, $t(257) = -3.09$, $p = .002$, 95% CI [-1.09, -.24], while the effect is insignificant for web recommender platforms. Therefore, both H_{3a} and H_{4a} are supported (see table 3).

Trustworthiness

The model explaining trustworthiness was significant, $R = .27$, $F(8, 257) = 2.58$, $p = .010$, with 7.4% ($R^2 = .074$) of the variance in trustworthiness explained. The main effect of the platforms' anthropomorphic cues was not significant. However, the main effect of the type of recommendation was significant, $b = -.51$, $t(257) = -2.25$, $p = .025$. The unconditional interaction effect of the platforms' anthropomorphic cues and the type of recommendation was not significant (see table 2).

Table 4. Conditional direct effects

		Trustworthiness		
		<i>b</i>	<i>t</i>	95% CI
Anthropomorphic cues	Customized	0.05 (0.22)	0.21	-0.39, 0.48
	Personalized	0.02 (0.23)	0.10	-0.43, 0.47
Type of recommendations	Recommender Agent	-0.53* (0.22)	-2.40	-0.97, -0.10
	Web Recommender Platform	-0.51* (0.23)	-2.25	-0.95, -0.06

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A test for conditional effects revealed that there were no significant effects of the platforms' anthropomorphic cues on trustworthiness for both customized and personalized

recommendations. Hence, both H_{1b} and H_{2b} are rejected. The test did find, however, that customized recommendations have a significant positive effect on trustworthiness for recommender agents, $b = -.53$, $t(257) = -2.40$, $p = .017$, 95% CI $[-.97, -.10]$, and web recommender platforms, $b = -.51$, $t(257) = -2.25$, $p = .025$, 95% CI $[-.95, -.06]$. Therefore, H_{3b} is supported, while H_{4b} is rejected (see table 4).

Perceived Risk

The model explaining perceived risk was significant, $R = .36$, $F(8, 257) = 4.75$, $p < .001$, with 12.9% ($R^2 = .129$) of the variance in perceived risk explained. The main effect of the platforms' anthropomorphic cues was not significant. However, the main effect of the type of recommendations on perceived risk, was significant, $b = .62$, $t(257) = 2.51$, $p = .013$. The unconditional interaction effect of the platforms' anthropomorphic cues and the type of recommendation was not significant (see table 2).

Table 5. Conditional direct effects

		Perceived risk		
		b	t	95% CI
Anthropomorphic cues	Customized	-0.25 (0.24)	-1.04	-0.73, 0.23
	Personalized	0.26 (0.25)	1.05	-0.23, 0.75
Type of recommendations	Recommender Agent	1.14*** (0.24)	4.66	0.66, 1.62
	Web Recommender Platform	0.62* (0.25)	2.51	0.13, 1.11

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A test for conditional effects revealed no significant effects of the platforms' anthropomorphic cues on perceived risk for both customized and personalized recommendations. Hence, both H_{1c} and H_{2c} are rejected. The test did find, however, that personalized recommendations have a significant positive effect on perceived risk, for recommender agents, b

$= 1.14$, $t(257) = 4.66$, $p < .001$, 95% CI [.66, 1.62], and web recommender platforms, $b = .62$, $t(257) = 2.51$, $p = .013$, 95% CI [.13, 1.11]. Therefore, H_{3c} is supported, while H_{4c} is rejected (see table 5).

Adherence to Recommendations

The overall model significantly explained users' adherence to recommendations, $R = .61$, $F(11, 254) = 13.33$, $p < .001$, with the model explaining 36.6% ($R^2 = .366$) of the variance in adherence to recommendations. When controlling for the anthropomorphic cues, types of recommendations, and their interaction term, all the mediators were found to have a significant direct effect on adherence to recommendations. These were perceived control, $b = .37$, $t(254) = 5.01$, $p < .001$; trustworthiness, $b = -.64$, $t(254) = -7.18$, $p < .001$; and perceived risk, $b = -.22$, $t(254) = -2.63$, $p = .009$. The model revealed that when controlling for the mediators, the platforms' anthropomorphic cues had a significant main effect on adherence to recommendations, $b = .82$, $t(254) = 3.32$, $p = .001$, while the type of recommendations did not. In addition, their interaction term had a significant unconditional direct effect on adherence to the recommendations, $b = -.73$, $t(254) = -2.05$, $\Delta R^2 = .01$, $\Delta F(1, 254) = 4.20$, $p = .042$ (see table 2).

Table 6. Conditional direct effects

		Adherence to Recommendations		
		<i>b</i>	<i>t</i>	95% CI
Anthropomorphic cues	Customized	0.82** (0.25)	3.32	0.34, 1.31
	Personalized	0.09 (0.25)	0.36	-0.41, 0.59
Type of recommendations	Recommender Agent	-0.77** (0.26)	-2.95	-1.28, -0.26
	Web Recommender Platform	-0.03 (0.26)	-0.13	-0.54, 0.47

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A test for conditional effects revealed that recommender agents had a significant positive direct effect on adherence to the recommendations for customized recommendations, $b = .82$, $t(254) = 3.32$, $p = .001$, 95% CI [.34, 1.31], while the effect is insignificant for personalized recommendations. Hence, H_{1d} is supported while H_{2d} is rejected. Additionally, customized recommendations had a significant positive direct effect on adherence to recommendations for recommender agents, $b = -.77$, $t(254) = -2.95$, $p = .004$, 95% CI [-1.28, -.26], while the effect is insignificant for web recommender platforms. Thus, both H_{3d} and H_{4d} are supported (see table 6).

To check for indirect effects and moderated mediation, 95% confidence intervals of 5000 bootstrapped samples (Preacher & Hayes, 2004) test for moderated mediation (see Hayes, 2015; 2018b) was conducted (see table 7).

Table 7. Conditional indirect effects

		Perceived control		Trustworthiness		Perceived risk	
		<i>b</i>	95% CI	<i>b</i>	95% CI	<i>b</i>	95% CI
Anthropomorphic cues	Customized	0.18 (0.09)	0.03, 0.38	0.03 (0.14)	-0.23, 0.32	-0.05 (0.06)	-0.21, 0.05
	Personalized	-0.05 (0.09)	-0.23, 0.12	0.01 (0.15)	-0.29, 0.31	0.06 (0.07)	-0.05, 0.22
Type of recommendations	Recommender Agent	-0.25 (0.10)	-0.48, -0.07	-0.34 (0.15)	-0.68, -0.07	0.25 (0.12)	0.03, 0.51
	Web Recommender Platform	-0.02 (0.08)	-0.19, 0.15	-0.33 (0.16)	-0.66, -0.03	0.13 (0.08)	0.01, 0.33

Mediated by Perceived Control

The test revealed that recommender agents had a significant positive indirect effect on adherence to recommendations through perceived control for customized recommendations, $b =$

.18, $SE = .09$, 95% CI [.29, .37], yet the effect was insignificant for personalized recommendations. The index of moderated mediation confirmed that the indirect effects significantly differed between customized and personalized recommendations, $b = -.23$, $SE = .13$, 95% CI [-.51, -.01]. Hence, H_{5a} is supported, while H_{6a} is rejected.

The test also demonstrated that customized recommendations had a significant indirect effect on adherence to recommendations through perceived control for recommender agents, $b = -.25$, $SE = .10$, 95% CI [-.47, -.07], yet the effect was insignificant for web recommender platforms. The index of moderated mediation confirmed that the indirect effects significantly differed between recommender agents and web recommender platforms, $b = -.23$, $SE = .13$, 95% CI [-.50, -.01]. Therefore, H_{7a} is supported.

Mediated by trustworthiness

The test revealed that there were no significant indirect effects between the platform's anthropomorphic cues on adherence to the recommendations through trustworthiness for both customized and personalized recommendations. Hence, H_{5b} and H_{6b} are rejected. However, customized recommendations showed significant positive indirect effects on adherence to the recommendations through trustworthiness for recommender agents, $b = -.34$, $SE = .15$, 95% CI [-.68, -.03], and web recommender platforms, $b = -.33$, $SE = .16$, 95% CI [-.67, -.03]. The index of moderated mediation demonstrated that the indirect effects did not significantly differ between recommender agents and web recommender platforms, $b = -.02$, $SE = .20$, 95% CI [-.45, .37]. Therefore, H_{7b} is rejected.

Mediated by perceived risk

The test revealed that there were no significant indirect effects between the platform's anthropomorphic cues on adherence to recommendations through perceived risk for both

customized and personalized recommendations. Hence, H_{5c} and H_{6c} are rejected. However, the test did find that personalized recommendations had a significant negative indirect effect on adherence to recommendations through perceived risk for recommender agents, $b = .25$, $SE = .12$, 95% CI [.04, .52], and web recommender platforms, $b = .13$, $SE = .08$, 95% CI [.01, .32]. The index of moderated mediation demonstrated that the indirect effects did not significantly differ between recommender agents and web recommender platforms, $b = .11$, $SE = .10$, 95% CI [-.03, .35]. Therefore, H_{7c} is rejected.

Discussion and Conclusions

The study assessed the extent to which recommender systems' anthropomorphic cues and the type of recommendations provided influenced users' perceptions of control, trustworthiness, and the risk of using it. The study examined how these perceptions, in turn, influence users' adherence to the recommendations. Recommender agents are widely available online, yet there is limited knowledge regarding the persuasive implications of their anthropomorphic cues on users' resistance to the platform and the provided recommendations. Moreover, there are gaps in the literature concerning proactive and reactive information disclosure in online marketing settings, especially when applied to recommender agents. The study, thus, aimed to contribute to the understanding of the influences anthropomorphic cues have on users' resistance to recommender systems. The results of an online experiment with recommender agents and web recommender platforms that provided customized or personalized recommendations yielded interesting findings on the matter.

The first key finding indicates that when receiving customized recommendations from a recommender agent, compared to personalized recommendations, one will be more likely to adhere to the recommendation, perceive to be in more control, and perceive the recommender

system to be more trustworthy and less risky. In turn, adherence to the recommendations is based on perceived control, trustworthiness, and perceived risk. The second key finding indicates that when receiving customized recommendations from a recommender agent, compared to a web recommender platform, one would be more likely to adhere to the recommendations and perceive to be in more control. In turn, one will also be more likely to adhere to the recommendations based on the perceived control.

These findings are meaningful in different aspects. First, in line with mind processing theory (Epley & Waytz, 2010; Gray et al., 2012; Waytz et al., 2010; Wegner, 2002), which explains that people ascribe mental capacities to anthropomorphic nonhuman entities and then react to and evaluate these based on their moral judgments and values, users perceived and evaluated recommender agents and the recommendations provided based on the moral value of the agent's actions. It provides evidence for the importance of recommender agents, and agents in general, to sustain positive moral mentality in their actions, as it can reduce users' resistance when anthropomorphic cues are available. This validates earlier research on recommender agents that demonstrated users' positive reactions to customized recommendations (Daniel et al., 2018). Accordingly, it can be said that anthropomorphic cues could trigger positive and persuasive reactions when the recommender agent's actions, and mentality conform to people's inherent social roles and norms.

These findings also extend the theoretical scope of disclosure with recommender agents. As users ascribed meaning to the recommender agent's actions, their disclosure to the recommender agent followed the expected social norms of interpersonal relations (Altman & Taylor, 1973; Jourard & Lasakow, 1958; Pearce & Sharp, 1973). When the disclosure was reactive and forced, it was reflected in users' resistance to the platform and to the

recommendations. On the contrary, proactive disclosures of users to recommender agents amplified users' positive perceptions towards the platform and their adherence to the recommendations. This supports earlier findings that demonstrated negative users' reactions to personalized recommendations by recommender agents (e.g., Puzakova et al., 2013; Sah & Peng, 2015). It can be implied from this study's results that anthropomorphic cues can also trigger negative reactions when the recommender agent's actions and mentality do not conform to people's inherent social roles and norms.

One additional key finding of the study should be taken into consideration when addressing the negative attributions of anthropomorphic cues. While it was expected that receiving personalized recommendations would lead users to demonstrate higher levels of resistance towards recommender agents than towards web recommender platforms, there were no differences between the two. Accordingly, it should be stressed that when the recommender agent's actions and mentality do not conform to people's inherent social roles and norms, users reacted to it as they would react to a recommender system that lacks anthropomorphic cues (i.e., web recommender platform).

The last key finding of the study indicates that when receiving personalized recommendations from a web recommender platform, compared to customized recommendations, there were no differences in users' perceived control and adherence to the recommendations. However, in this case, one will perceive the platform as less trustworthy and riskier, and in turn, would be less likely to adhere to the recommendations. Moreover, when receiving customized recommendations, there were no differences between the platforms regarding users' perceptions of trust or risk.

These findings contradict earlier studies (e.g., Barth & de Jong, 2017; Beresford et al., 2012; Carrascal et al., 2013; Hann et al., 2007; Joinson et al., 2010) that addressed online marketing procedures under the frameworks of social exchange theory (Homans, 1961) and privacy paradox (Barnes, 2006), where users evaluate an exchange based on cost and reward cues (Ekeh, 1974; Homans, 1961; Lambe et al., 2001; Lawler, 2001; Lawler & Thye, 1999). A potential explanation could be that users need more systematic cues to evaluate the recommendations provided by web recommender platforms, as they look for pieces of information to assess the recommendations (Chaiken, 1980; Chen, Duckworth, & Chaiken, 1999; Eagly & Chaiken, 1993) in terms of costs and rewards (Ekeh, 1974; Homans, 1961; Lambe et al., 2001; Lawler, 2001; Lawler & Thye, 1999).

Based on the findings of this study, it can be argued that when web recommender platforms lack sufficient cues to indicate the reward from the exchange (e.g., users' ratings, distance, users' reviews), users are limited in their evaluations and are prone to pick up on cues indicating the cost (e.g., disclosure). Therefore, users demonstrated higher resistance to personalized recommendations, compared to customized recommendations, when using web recommender platforms. Nonetheless, future research should refine these results by evaluating user resistance to web recommender systems when cues indicating rewards from the exchange are presented against cues indicating the costs.

Finally, these findings highlight that, while anthropomorphic cues can contribute to interactions with recommender systems and reduce potential resistance, the type of recommendation provided has a substantial impact on resistance. This aligns with earlier research that has addressed the persuasive implications of tailoring techniques and demonstrated the differences between customization and personalization (e.g., Arora et al., 2008; Baek &

Morimoto, 2012; Chellappa & Sin, 2005; Kalyanaraman & Sundar, 2006; Kaptein et al., 2015; Treiblmaier et al., 2004; Sundar & Marathe, 2010; Wang et al., 2018). It can, thus, be concluded that users' positive experiences when using recommender systems and adhering to recommendations is conditional based on recommendations being customized and in line with their proactive disclosure. When the recommender system demonstrates anthropomorphic cues, the positive influence of customized recommendations can be amplified, reducing users' potential resistance towards the platform and the recommendations.

Limitations and Future Research

There are several limitations to take into consideration. First, the use of simulated recommender systems in a single-treatment online experimental design; participants used recommender platforms that were designed specifically for this study. Being a hypothetical simulation, participants' engagement might have been limited such that they lacked the internal motivations to be engaged in a simulated commercial behavior that has no impact on their life outside of the study. Participants were given recommendations about fictional restaurants, and accordingly, their reaction to the manipulations could be restrained and not reflective of their potential reactions in commercial settings. Moreover, while the act of personalization was explicitly stressed to trigger reactions, the recommender systems were restricted from retrieving actual user information to personalize recommendations.

These simulations might not correspond with realistic personalization situations or trigger precisely the same reactions that users would demonstrate in naturalistic settings with a commercial recommender system. However, using these simulations allows us to study resistance to recommender systems while complying with ethical considerations and not

collecting participants' personal information. Furthermore, the use of a single-treatment online experimental design allowed for the collection of a fair sample size and minimal dropout rate.

Future research could target these limitations and extend these findings by employing a longitudinal design using agent or web simulations as ecological momentary assessments. By conducting the study overtime in more naturalistic settings, the simulations could correspond to users' expectations and reflect their reality. In addition, it could elicit information from participants that could be used for simulating conditions of personalized recommendations in more individualistic terms without compromising participants' privacy. Future research is also encouraged partner with corporations, providing recommendations for real products to correspond with the commercial settings of the studied phenomena.

Another limitation that needs to be addressed is that the design of recommender systems can influence users' reactions. To avoid any possible influence of design cues in the manipulation, and reduce any artificial differences between the conditions, the web recommender platform design was minimalistic. However, this could be a limitation considering that the design features were not reflective of current designs of web recommender platforms. Likewise, the simplistic design could also be reflected in participants' evaluations of the platform and the provided recommendations. To reduce any potential threat to the internal validity of the study, participants' perceptions of the manipulations' realism were controlled in both manipulation checks, and when diagnosing the sample for outliers. Future research should further address this by evaluating current design patterns of web recommender systems and designing the manipulation accordingly. If possible, future research should conduct a pretest with various design options to counter any potential impact of design cues before conducting the experiment.

References

- Altman, I., & Taylor, D. A. (1973). *Social penetration: The development of interpersonal relationships*. Oxford, England: Holt, Rinehart & Winston.
- Araujo, T. (2020). Conversational Agent Research Toolkit: An alternative for creating and managing chatbots for experimental research. *Computational Communication Research*. 2.1. (pp 35-51). doi: 10.31235/osf.io/9ukyf
- 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. doi:10.1016/j.chb.2018.03.051
- Archer, R. L., & Berg, J. H. (1978). Disclosure reciprocity and its limits: A reactance analysis. *Journal of Experimental Social Psychology*, 14(6), 527-540. doi:10.1016/0022-1031(78)90047-1
- Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., . . . Zhang, Z. J. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Letters*, 19(3), 305. doi:10.1007/s11002-008-9056-z
- Baek, T. H., & Morimoto, M. (2012). Stay away from me. *Journal of Advertising*, 41(1), 59-76. doi:10.2753/JOA0091-3367410105
- Barnes, S. (2006). A privacy paradox: Social networking in the United States. *First Monday*, 11(9). doi: 10.5210/fm.v11i9.1394
- Barth, S., & de Jong, M. D. T. (2017). The privacy paradox – investigating discrepancies between expressed privacy concerns and actual online behavior – A systematic literature review. *Telematics and Informatics*, 34(7), 1038-1058. doi:10.1016/j.tele.2017.04.013

- Bartneck, C., Kulic', D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, 1(1), 71-81. doi:10.1007/s12369-008-0001-3
- Beresford, A. R., Kübler, D., & Preibusch, S. (2012). Unwillingness to pay for privacy: A field experiment. *Economics Letters*, 117(1), 25-27. doi:https://doi.org/10.1016/j.econlet.2012.04.077
- Brehm, S. S., & Brehm, J. W. (1981). *Psychological reactance*. Academic Press.
- Cacioppo, J. T., Petty, R. E., & Feng Kao, C. (1984). The efficient assessment of need for cognition. *Journal of Personality Assessment*, 48(3), 306-307. doi:10.1207/s15327752jpa4803_13
- Carrascal, J. P., Riederer, C., Erramilli, V., Cherubini, M., & de Oliveira, R. (2013). (2013). Your browsing behavior for a big mac: Economics of personal information online. Paper presented at the *Proceedings of the 22nd International Conference on World Wide Web*, Rio de Janeiro, Brazil. 189-200. doi:10.1145/2488388.2488406
- Cassell, J., & Bickmore, T. (2000). External manifestations of trustworthiness in the interface. *Communications of the ACM*, 43(12), 50-56. doi:10.1145/355112.355123
- Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology*, 39(5), 752-766. doi:10.1037/0022-3514.39.5.752
- Chang, Y., Wong, S. F., & Lee, H. (2015). (2015). Understanding perceived privacy: A privacy boundary management model. Paper presented at the *Pacis*, 78. Retrieved from <http://aisel.aisnet.org/pacis2015/78>

- Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management*, 6(2), 181-202.
doi:10.1007/s10799-005-5879-y
- Chen, S., Duckworth, K., & Chaiken, S. (1999). Motivated heuristic and systematic processing. *Psychological Inquiry*, 10(1), 44-49. doi:10.1207/s15327965pli1001_6
- Chen, Q., Feng, Y., Liu, L., & Tian, X. (2019). Understanding consumers' reactance of online personalized advertising: A new scheme of rational choice from a perspective of negative effects. *International Journal of Information Management*, 44, 53-64.
doi:10.1016/j.ijinfomgt.2018.09.001
- Christakopoulou, K., Radlinski, F., & Hofmann, K. (2016, August). Towards conversational recommender systems. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 815-824). doi: 10.1145/2939672.2939746.
- Cofta, P. (2007). Confidence, trust and identity. *BT Technology Journal*, 25(2), 173-178.
doi:10.1007/s10550-007-0042-4
- Conner, D. (1992). *Managing at the Speed of Change: How Resilient Managers Succeed and Prosper Where Others Fail*, 1st Edn. New York: Villard Books
- Cross, E. S., Ramsey, R., Liepelt, R., Prinz, W., & Hamilton, A. F. D. C. (2016). The shaping of social perception by stimulus and knowledge cues to human animacy. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 371(1686). doi: 10.1098/rstb.2015.0075
- Daniel, F., Matera, M., Zaccaria, V., & Dell'Orto, A. (2018). (2018). Toward truly personal chatbots: On the development of custom conversational assistants. Paper presented at the *1st International*

Workshop on Software Engineering for Cognitive Services (SE4COG), Gothenburg, Sweden. 31-36. doi:10.1145/3195555.3195563

de Ruyter, K., Wetzels, M., & Kleijnen, M. (2001). Customer adoption of e-service: An experimental study. *International Journal of Service Industry Management*, 12(2), 184-207.
doi:10.1108/09564230110387542

de Visser, E. J., Monfort, S. S., McKendrick, R., Smith, M. A. B., McKnight, P. E., Krueger, F., & Parasuraman, R. (2016). Almost human: Anthropomorphism increases trust resilience in cognitive agents. *Journal of Experimental Psychology: Applied*, 22(3), 331-349.
doi:10.1037/xap0000092

Debatin, B., Lovejoy, J. P., Horn, A., & Hughes, B. N. (2009). Facebook and online privacy: Attitudes, behaviors, and unintended consequences. *Journal of Computer-Mediated Communication*, 15(1), 83-108. doi:10.1111/j.1083-6101.2009.01494.x

Delbaere, M., McQuarrie, E. F., & Phillips, B. J. (2011). Personification in advertising: Using a visual metaphor to trigger anthropomorphism. *Journal of Advertising*, 40(1), 121-130.
doi:10.2753/JOA0091-3367400108

Deloitte. (2019, November 27). Conversational AI: Deloitte Australia: Consulting. Retrieved from <https://www2.deloitte.com/au/en/pages/strategy-operations/articles/conversational-AI.html>

Derlega, V. J., Harris, M. S., & Chaikin, A. L. (1973). Self-disclosure reciprocity, liking and the deviant. *Journal of Experimental Social Psychology*, 9(4), 277-284. doi:10.1016/0022-1031(73)90065-6

- Dinev, T., & Hart, P. (2005). Internet privacy concerns and social awareness as determinants of intention to transact AU -. *International Journal of Electronic Commerce*, 10(2), 7-29.
doi:10.2753/JEC1086-4415100201
- Dinev, T., Xu, H., Smith, J. H., & Hart, P. (2013). Information privacy and correlates: An empirical attempt to bridge and distinguish privacy-related concepts. *European Journal of Information Systems*, 22(3), 295-316. doi:10.1057/ejis.2012.23
- Dowling, G. R., & Staelin, R. (1994). A model of perceived risk and intended risk-handling activity. *Journal of Consumer Research*, 21(1), 119-34. doi:10.1086/209386
- Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*. Orlando, FL, US: Harcourt Brace Jovanovich College Publishers.
- Edison, S. W., & Geissler, G. L. (2003). Measuring attitudes towards general technology: Antecedents, hypotheses and scale development. *Journal of Targeting, Measurement and Analysis for Marketing*, 12(2), 137-156. doi:10.1057/palgrave.jt.5740104
- Ekeh, P. (1974). *Social exchange theory: The two traditions*. Cambridge, Massachusetts: Harvard University Press.
- Epley, N., & Waytz, A. (2010). Mind perception. In S. T. Fiske, D. T. Gilbert & G. Lindsey (Eds.), *Handbook of social psychology* (5th ed.) John Wiley and Sons Ltd.
doi:10.1002/9780470561119.socpsy001014
- Epley, N., Waytz, A., Akalis, S., & Cacioppo, J. T. (2008). When we need A human: Motivational determinants of anthropomorphism. *Social Cognition*, 26(2), 143-155.
doi:10.1521/soco.2008.26.2.143

Eyssel, F, Kuchenbrandt, D., & Bobinger, S. (2011). Effects of anticipated human-robot interaction and predictability of robot behavior on perceptions of anthropomorphism. Paper presented at the *2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 61-67.

doi:10.1145/1957656.1957673

Eyssel, F, de Ruiter, L., Kuchenbrandt, D., Bobinger, S., & Hegel, F. (2012). 'If you sound like me, you must be more human': On the interplay of robot and user features on human-robot acceptance and anthropomorphism. Paper presented at the *2012 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 125-126. doi:10.1145/2157689.2157717

Facebook IQ. (2018, February 26). Topics to Watch in the United States for January 2018. Retrieved from https://www.facebook.com/business/news/insights/2018-01-topics-to-watch-united-states?ref=search_new_0#Chatbot

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149-1160. doi:10.3758/BRM.41.4.1149

Faul, F., Erdfelder, E., Lang, A., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175-191. doi:10.3758/BF03193146

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451-474. doi:10.1016/S1071-5819(03)00111-3

Forrester Consulting. (2019, May). Study: Use Automation, AI, And Chatbots To Improve Customer Engagements. Retrieved from <https://www.liveperson.com/resources/news/forrester-tlp/>

- Fransen, M. L., Smit, E. G., & Verlegh, P. W. J. (2015). Strategies and motives for resistance to persuasion: An integrative framework. *Frontiers in Psychology*, 6, 1201; 1201-1201. doi:10.3389/fpsyg.2015.01201
- Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-commerce and the importance of social presence: Experiments in e-products and e-services. *Omega*, 32(6), 407-424. doi:10.1016/j.omega.2004.01.006
- Gerck, E. (2002). Trust as qualified reliance on information, part I. *The COOK Report on Internet*, ISSN 1071 - 6327, Vol. X, 19-24. doi:10.13140/RG.2.2.22646.04165
- Gray, K., Young, L., & Waytz, A. (2012). Mind perception is the essence of morality. *Psychological Inquiry*, 23(2), 101-124. doi:10.1080/1047840X.2012.651387
- 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. doi:10.1080/08839514.2013.835230
- Hann, I., Hui, K., Lee, S. T., & Png, I. P. L. (2007). Overcoming online information privacy concerns: An information-processing theory approach. *Journal of Management Information Systems*, 24(2), 13-42. doi:10.2753/MIS0742-1222240202
- Hart, P., & Royne, M. B. (2017). Being human: How anthropomorphic presentations can enhance advertising effectiveness. *Journal of Current Issues & Research in Advertising*, 38(2), 129-145. doi:10.1080/10641734.2017.1291381
- Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, 50(1), 1-22. doi:10.1080/00273171.2014.962683

- Hayes, A. F. (2018a). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach Second Edition*. New York: Guilford Press.
- Hayes, A. F. (2018b). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs*, 85(1), 4-40.
doi:10.1080/03637751.2017.1352100
- Holtgraves, T. M., Ross, S. J., Weywadt, C. R., & Han, T. L. (2007). Perceiving artificial social agents. *Computers in Human Behavior*, 23(5), 2163-2174. doi:10.1016/j.chb.2006.02.017
- Homans, G. C. (1961). *Social behavior: Its elementary forms*. Oxford, England: Harcourt, Brace.
- Huberman, B. A., Adar, E., & Fine, L. R. (2005). Valuating privacy. *IEEE Security & Privacy*, 3(5), 22-25. doi:10.1109/MSP.2005.137
- Jain, S. P., & Posavac, S. S. (2004). Valenced comparisons. *Journal of Marketing Research*, 41(1), 46-58. doi:10.1509/jmkr.41.1.46.25080
- Joinson, A. N., Reips, U., Buchanan, T., & Schofield, C. B. P. (2010). Privacy, trust, and self-disclosure online. *Human-Computer Interaction*, 25(1), 1-24. doi:10.1080/07370020903586662
- Jourard, S. M., & Lasakow, P. (1958). Some factors in self-disclosure. *The Journal of Abnormal and Social Psychology*, 56(1), 91-98. doi:10.1037/h0043357
- King, J. (2015). Understanding Privacy Decision Making Using Social Exchange Theory. In *CSCW '15*
- Kalyanaraman, S., & Sundar, S. S. (2006). The psychological appeal of personalized content in web portals: Does customization affect attitudes and behavior? *Journal of Communication*, 56(1), 110-132. doi:10.1111/j.1460-2466.2006.00006.x

- Kaptein, M., Markopoulos, P., de Ruyter, B., & Aarts, E. (2015). Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles. *International Journal of Human-Computer Studies*, 77, 38-51. doi:10.1016/j.ijhcs.2015.01.004
- Kojouharov, S. (2018, January 24). How Businesses are Winning with Chatbots & Ai – Chatbots Life. Retrieved from <https://chatbotslife.com/how-businesses-are-winning-with-chatbots-ai-5df2f6304f81>
- Laban, G., & Araujo, T. (2020). Working Together with Conversational Agents: The Relationship of Perceived Cooperation with Service Performance Evaluations. In Følstad A. et al. (eds) *Chatbot Research and Design. CONVERSATIONS 2019. Lecture Notes in Computer Science*, vol 11970. (pp. 215-228). Springer, Cham. doi:10.1007/978-3-030-39540-7_15
- Laban, G., George, J. N., Morrison, V., & Cross, E. S. (2020). Tell Me More! Assessing Interactions with Social Robots From Speech. doi:10.31234/osf.io/jkht2
- Laban, G., Morrison, V., & Cross, E. S. (2020, March). Let's Talk About It! Subjective and Objective Disclosures to Social Robots. In Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction (pp. 328-330). doi:10.1145/3371382.3378252
- Laksmidewi, D., Susianto, H., & Afiff, A. Z. (2017). Anthropomorphism in advertising: The effect of anthropomorphic product demonstration on consumer purchase intention. *Asian Academy of Management Journal*, 22(1), 1. doi:10.21315/aamj2017.22.1.1
- Lambe, C. J., Wittmann, C. M., & Spekman, R. E. (2001). Social exchange theory and research on business-to-business relational exchange. *Journal of Business-to-Business Marketing*, 8(3), 1-36. doi:10.1300/J033v08n03_01

- Lawler, E. J. (2001). An affect theory of social exchange. *American Journal of Sociology*, 107(2), 321-352. doi:10.1086/324071
- Lawler, E. J., & Thye, S. R. (1999). Bringing emotions into social exchange theory. *Annual Review of Sociology*, 25(1), 217-244. doi:10.1146/annurev.soc.25.1.217
- Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information Systems Research*, 15(4), 336-355. doi:10.1287/isre.1040.0032
- McCarthy, A. (2017, February 27). If Anyone Is Going to Buy Directly from a Chatbot, It's Millennials. Retrieved from <https://retail.emarketer.com/article/anyone-going-buy-directly-chatbot-its-millennials/58b5c084ebd4000a60315ecf>
- McGill, A. L., & Kim, S. (2011). Gaming with mr. slot or gaming the slot machine? power, anthropomorphism, and risk perception. *Journal of Consumer Research*, 38(1), 94-107. doi:10.1086/658148
- Modgil, N. (2018, November 02). How ChatBots have Become More 'Personalized' and Less 'Robotic'. Retrieved from <https://www.entrepreneur.com/article/322716>
- Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, 56(1), 81-103. doi:10.1111/0022-4537.00153
- Pearce, W. B., & Sharp, S. M. (1973). Self-disclosing communication. *Journal of Communication*, 23(4), 409-425. doi:10.1111/j.1460-2466.1973.tb00958.x
- Peppers, D. and Rogers, M. (1997). *Enterprise One to One*. Currency/Doubleday, New York, NY.

- Peppers, D., Rogers, M., & Dorf, B. (1999). Is your company ready for one-to-one marketing? *Harvard Business Review*, 77, 151-60.
- Petty, R. E., & Cacioppo, J. T. (1979). Issue involvement can increase or decrease persuasion by enhancing message-relevant cognitive responses. *Journal of Personality and Social Psychology*, 37(10), 1915-1926. doi:10.1037/0022-3514.37.10.1915
- Petty, R. E., Tormala, Z. L., & Rucker, D. D. (2004). Resisting persuasion by counterarguing: An attitude strength perspective. In J. T. Jost, M. R. Banaji & D. A. Prentice (Eds.), *APA science series. APA decade of behavior series. Perspectivism in social psychology: The yin and yang of scientific progress* (pp. 37-51). Washington, DC, US: American Psychological Association. doi:10.1037/10750-004
- Powers, A., & Kiesler, S. (2006). The advisor robot: Tracing people's mental model from a robot's physical attributes. Paper presented at the *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction (HRI '06)*, ACM, New York, NY, USA. 218-225. doi:10.1145/1121241.1121280
- Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, 36(4), 717-731. doi:10.3758/BF03206553
- Premack, D., & Woodruff, G. (1978). Does the chimpanzee have a theory of mind? *Behavioral and Brain Sciences*, 1(4), 515-526. doi:10.1017/S0140525X00076512
- Puzakova, M., Kwak, H., & Rocereto, J. F. (2013). When humanizing brands goes wrong: The detrimental effect of brand anthropomorphization amid product wrongdoings. *Journal of Marketing*, 77(3), 81-100. doi:10.1509/jm.11.0510

- 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. doi: 10.2753/MIS0742-1222250405.
- Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender systems: Introduction and challenges. *Recommender systems handbook* (pp. 1-34) Springer. doi:10.1007/978-1-4899-7637-6
- Russell, D. (1982). The causal dimension scale: A measure of how individuals perceive causes. *Journal of Personality and Social Psychology*, 42(6), 1137-1145. doi:10.1037/0022-3514.42.6.1137
- Sah, Y. J., & Peng, W. (2015). Effects of visual and linguistic anthropomorphic cues on social perception, self-awareness, and information disclosure in a health website. *Computers in Human Behavior*, 45, 392-401. doi:10.1016/j.chb.2014.12.055
- Salonen, V., & Karjaluo, H. (2016). Web personalization: The state of the art and future avenues for research and practice. *Telematics and Informatics*, 33(4), 1088-1104. doi:10.1016/j.tele.2016.03.004
- Shaffer, G., & Zhang, Z. J. (1995). Competitive coupon targeting. *Marketing Science*, 14(4), 395-416. doi:10.1287/mksc.14.4.395
- Shawar, B. A., & Atwell, E. (2007). Chatbots: Are they really useful? *Ldv Forum*, 22(1), 29-49.
- Sun, X., May, A., & Wang, Q. (2016). The impact of user- and system-initiated personalization on the user experience at large sports events. *Applied Ergonomics*, 54, 1-9. doi:https://doi.org/10.1016/j.apergo.2015.11.001

- Sundar, S. S., & Marathe, S. S. (2010). Personalization versus customization: The importance of agency, privacy, and power usage. *Human Communication Research*, 36(3), 298-322.
doi:10.1111/j.1468-2958.2010.01377.x
- Sundar, S. S. (2020). Rise of Machine Agency: A Framework for Studying the Psychology of Human–AI Interaction (HAII). *Journal of Computer-Mediated Communication*, 25(1), 74-88.
doi: 10.1093/jcmc/zmz026.
- Treiblmaier, H., Madlberger, M., Knotzer, N., & Pollach, I. (2004). (2004). Evaluating personalization and customization from an ethical point of view: An empirical study. Paper presented at the *Proceedings of the 37th Annual Hawaii International Conference on System Sciences (HICSS'04)*, 7, 10 pp. doi:10.1109/HICSS.2004.1265434
- Utz, S., & Krämer, N. C. (2009). The privacy paradox on social network sites revisited: The role of individual characteristics and group norms. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 3(2), article 2. Retrieved from
<https://cyberpsychology.eu/article/view/4223/3265>
- Wang, C., Zheng, Y., Jiang, J., & Ren, K. (2018). Toward privacy-preserving personalized recommendation services. *Engineering*, 4(1), 21-28. doi:10.1016/j.eng.2018.02.005
- Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human?: The stability and importance of individual differences in anthropomorphism. *Perspect Psychol Sci*, 5(3), 219-232.
doi:10.1177/1745691610369336
- Wegner, D. M. (2002). *The illusion of conscious will*. Cambridge, MA: MIT Press.

Weiner, B. (1979). A theory of motivation for some classroom experiences. *Journal of Educational Psychology*, 71(1), 3-25. doi:10.1037/0022-0663.71.1.3

Wu, K., Huang, S. Y., Yen, D. C., & Popova, I. (2012). The effect of online privacy policy on consumer privacy concern and trust. *Computers in Human Behavior*, 28(3), 889-897. doi:10.1016/j.chb.2011.12.008

Zhang, B., & Sundar, S. S. (2019). Proactive vs. reactive personalization: Can customization of privacy enhance user experience?. *International Journal of Human-Computer Studies*, 128, 86-99. doi: 10.1016/j.ijhcs.2019.03.002.