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Machine gaze in online behavioral targeting: The effects of algorithmic human likeness on social presence and social influence

Bingjie Liu [a,*], Lewen Wei [b,c]

[a] Department of Communication Studies, California State University, Los Angeles, Music Building 105, 5151 State University Drive, CA, 90032, USA
[b] Donald P. Bellisario College of Communications, Pennsylvania State University, USA
[c] Gamification Group, Faculty of Information Technology and Communication Sciences, Tampere University, Finland

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ABSTRACT

Digital platforms increasingly use online behavioral targeting (OBT) to enhance consumers' engagement, which involves using algorithms to "gaze" at consumers—tracking their online activities and inferring their preferences—so as to deliver relevant, personalized messages (e.g., advertisements, recommendations) to consumers. In light of the rising call for algorithmic transparency, this study investigates the effects of algorithmic transparency on consumers' experience of social presence and OBT effectiveness, when the OBT algorithm has low or high level of similarity to humans' conscious mental processes. A one-factor, three-level (no transparency, vs. "observer" algorithm, vs. "judge" algorithm) online experiment with 209 participants was conducted. Results show that for individuals with low anthropomorphism tendency, the "observer" algorithm that did not form meaningful representations of consumers (i.e., low cognitive similarity to humans) reduced social presence, thereby compromising OBT effectiveness. The algorithm that "judged" consumers on meaningful dimensions (i.e., high cognitive similarity to humans) had no such effects. Findings suggest that anthropomorphism, as an important psychological mechanism underlying consumers' interaction with OBT platforms, may be inhibited by algorithmic transparency. Theoretical implications for understanding individuals' experience with OBT and human-machine communication in general and practical implications for designing algorithmic transparency in OBT practices are discussed.

1. Introduction

Interaction with algorithms is becoming a common part of consumers' experience with digital media. To boost consumer engagement, digital platforms (e.g., Facebook, Google, and Netflix) increasingly use online behavioral targeting (OBT)—the practice of delivering relevant, personalized messages to consumers based on the analysis of their online behaviors and sometimes other available metrics such as demographics and geographic data (Boerman et al., 2017; Nill & Aalberts, 2014). Essential to this practice is using machine learning algorithms to monitor consumers and make inferences about their characteristics and preferences, subjecting consumers to the algorithms' "gaze," an act involving not only seeing but also interpreting (Lacan, 1977). How do consumers respond to a machine's "gaze"? How might such an experience further influence their evaluations of the algorithm-selected messages and persuasion outcomes of OBT?

Existing theories and research in human-machine communication (HMC) suggest that humans tend to mindlessly anthropomorphize the media technologies they interact with, that is, to attribute humans' mental capacities and states to technologies (Epley et al., 2007; Kim & Sundar, 2012), even when the technologies have no humanlike looks (e.g., computers and websites). Such a tendency of anthropomorphism has been found to facilitate the experience of social presence during HMC, that is, to experience the technologies as intelligent, humanlike beings (Lee, 2004; Lombard & Xu, 2021), which is often linked to greater social influence by the technologies (Blascovich, 2002). Accordingly, in OBT contexts, a similar chain of responses can be expected such that when consumers are analyzed by the OBT algorithms and receiving personalized messages such as advertisements (ads) or recommendations, they may perceive the OBT algorithms' gaze through the lens of anthropomorphism and experience social presence—to perceive that they are gazed at by an intelligent being who makes inferences about who they are and pick items they might like.

Anthropomorphism involves perceiving humanlike states in

* Corresponding author.
E-mail addresses: bliu3@calstatela.edu (B. Liu), lpw5086@psu.edu, lewen.wei@tuni.fi (L. Wei).

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nonhuman agents, which occurs in part due to individuals' lack of accurate knowledge about the nonhuman agents, when egocentric or anthropocentric knowledge serves as a convenient (but inaccurate) guide for their interaction with the agents (Epley et al., 2007; Waytz, Morewedge, et al., 2010). What will happen then, if individuals are made aware of the *actual* stats of the nonhuman agents? Increasingly, OBT platforms are expected to be transparent about their algorithms in terms of *how* they analyze consumer data, that is, what the personalization is based on and how they evaluate, judge, and form impressions of consumers. Typically, algorithms in use for personalization are results of machine learning, which often follow processes that differ from humans' conscious mental processes involved in interpersonal impression formation and personalization (Mittelstadt et al., 2016). Given the apparent difference between algorithmic processes and human logic, will algorithmic transparency render the nonhumanness of the OBT algorithms salient to the consumers, make them more mindful of the fact that they are not working with a humanlike being, and thereby inhibit mindless anthropomorphism and the experience of social presence? Will the effectiveness of OBT in terms of consumers' attitudes and behavioral intentions toward the personalization also be influenced? Answers to these questions are key to understanding consumers' experience with transparent OBT practice and will provide practical suggestions for designers of OBT platforms. Against this backdrop, the current study set out to explore the effects of disclosing algorithmic processes on consumer experience and the role of anthropomorphism in shaping persuasion outcomes of OBT.

2. Literature review

2.1. Anthropomorphism: Definition, mechanisms, and outcomes

Before discussing the effects of algorithmic transparency in the context of OBT, we first explicate the concept of anthropomorphism by clarifying its definition, mechanisms, and its relationship with other key constructs in the current study as suggested by extant theories and research.

Anthropomorphism is a psychological process whereby people imbue the behaviors of other nonhuman agents with humanlike characteristics, such as motivations, intentions, and underlying mental states (see Epley et al., 2007; Gray et al., 2007). So far, anthropomorphism has been established as a common, natural response to nonhuman entities including but not limited to technological gadgets (e.g., websites, robots, computers) (e.g., Nass & Moon, 2000; Reeves & Nass, 1996), animals (Gray et al., 2007), celestial bodies (Waytz, Cacioppo et al., 2007), and even animated, abstract shapes (Heider & Simmel, 1944; Waytz, Cacioppo, & Epley, 2010).

Although early researchers used the term *anthropomorphism* to refer to one's "thoughtful, sincere belief that [an] object has human characteristics" (e.g., Nass & Moon, 2000, p. 93; Reeves & Nass, 1996), research later has shown that anthropomorphism can also be a mindless, unconscious process that is elicited automatically when individuals see or interact with nonhuman agents ranging from animals, to natural disasters, to technological gadgets and platforms, even when they bear little morphological similarity to humans (e.g., Epley et al., 2008; Kim & Sundar, 2012; Waytz, Morewedge, et al., 2010). For example, although an alarm clock does not look like a human, participants in previous studies still perceived it to have "a mind of its own," "intentions," and "free will" to a certain degree (Epley et al., 2008; Waytz, Morewedge, et al., 2010). When interacting with a website that provided information on skin cancer, participants still found adjectives such as "sociable," "friendly," and "personal" appropriate to describe the website (Kim & Sundar, 2012).

In addition, such self-reported anthropomorphism is no mere metaphor. As demonstrated in neuroimaging studies, using fMRI, Gazzola et al. (2007) found that the mirror neuron system (i.e., the neural system involved in human social interactions) was activated by the sight of an industrial robot's actions as strongly as by the sight of human actions. Waytz, Morewedge, and colleagues (2010, Study 3) found that vMPFC (the brain region involved in inferring others' mental states during human-human interaction) became significantly more active when participants were induced to anthropomorphize 32 different technological gadgets (e.g., alarm clock, MP3 player, computer keyboard, etc.), which also corresponded to participants' self-reported anthropomorphism in the same study.

How and why does anthropomorphism happen? The three-factor theory of anthropomorphism identifies two motivational factors and one cognitive mechanism driving the process of anthropomorphism (Epley et al., 2007). The two fundamental human motivations include the motivation to understand or to explain the (imagined or actual) behaviors of others (i.e., the effectance motivation, Waytz, Morewedge, et al., 2010) and the motivation for social connection (i.e., the sociality motivation, Epley et al., 2008). The cognitive mechanism underlying anthropomorphism is the elicited agent knowledge, that is, the acquisition, activation, and application of anthropocentric knowledge elicited by the agent being perceived. For example, a nonhuman agent with more humanlike characteristics may elicit more knowledge about a prototypical human for the perceivers, thereby leading the perceivers to apply such knowledge to guide their interaction with the agent and attribute human mental states to it to a greater degree. Empirical studies so far support these propositions of the three-factor theory of anthropomorphism (for a review, Epley, 2014).

The cognitive mechanism identified in the three-factor theory of anthropomorphism is particularly relevant to the current study on the effects of transparency of OBT algorithms. As OBT platforms disclose their algorithmic processes to consumers, the elicited knowledge among consumers may be different from that in the non-transparent condition and may also vary as a function of the nature of the algorithms in use. As a result, the process of anthropomorphism may be facilitated or inhibited by the elicited knowledge and may then further influence consumers' experience and persuasion outcomes of OBT.

Anthropomorphism can facilitate other social perceptions and behaviors during humans' interaction with machines. As Waytz, Cacioppo, and Epley (2010) noted, "perceiving an agent to have a mind means that the agent is capable of observing, evaluating, and judging a perceiver, thereby serving as a source of normative social influence on the perceiver" (p. 222). As such, an immediate perceptual outcome of anthropomorphism is social presence, defined as a psychological state in which individuals experience an artificial object (e.g., a computer) as an intelligent being, with or without conscious awareness (Lee, 2004; Lee et al., 2006; Lombard & Xu, 2021).

As found in empirical research, when individuals interact with a machine and attribute humans' mental states to it as a result of the machine's anthropomorphic cues (e.g., high morphological similarity to humans, being controlled by humans, and being programmed by humans to follow human logic), they may feel as if they are interacting with an intelligent being (i.e., social presence) (for a review, see Lombard & Xu, 2021). Research has also found that compared to non-anthropomorphic technology, anthropomorphized technology induced higher level of social presence (e.g., Han, 2021; Kuosmanen, 2020; Qiu & Benbasat, 2009), led to higher engagement and greater attention during the interaction (which are indicators of social presence, Nass et al., 1995), and elicited more social influence and social responses (e.g., maintaining a larger physical distance in virtual environment, for a review, see Blascovich, 2002). Although not all studies measured social presence explicitly or in the exact same fashion, theoretically one's social responses to the technology indicate their experience of social presence—the perception of interacting with an intelligent being that merits social responses (Lombard & Xu, 2021).

2.2. Default response to machine gaze: Anthropomorphism and social presence

The discussion of anthropomorphism and social presence can be well applied to consumers' interaction with algorithms in the context of OBT, where algorithms are used to gaze at consumers for social influence. An algorithm is "[a] logical series of steps for organizing and acting on a body of data to quickly achieve a desired outcome" (Gillespie, 2016, p. 19). In OBT practices, the personalization algorithms determine what data are collected, how consumers are represented, and what messages are ultimately delivered. Typically, OBT platforms only disclose the fact that they are tracking consumers' online behaviors for personalization but are non-transparent about their algorithmic process in terms of *how* the personalization is realized. Based on extant theories and research, we argue that without informing consumers about the algorithmic process of OBT, an OBT platform will trigger a higher level of anthropomorphism as compared with the scenarios where the algorithmic process is revealed, which has downstream implications for consumers' experience of social presence, attitudes to the personalization, and the persuasion outcomes of OBT.

Before discussing how transparency of the algorithmic process may influence consumer experience, we first discuss how consumers respond to machine gaze in the default, black-box condition when they are unaware of *how* the machines analyze their behavioral data and make inferences about them. Social psychology research suggests that when individuals interact with unfamiliar others, one's *self* often serves as the default concept for reasoning about the unfamiliar agents in the absence of disconfirming experience (e.g., Davis et al., 1986; Gordon, 1986; Meltzoff, 2007; Nickerson, 1999). In other words, during HMC, individuals should by default model their machine partner's internal states based on a simulation of and generalization from their own minds, leading to the activation and application of egocentric or anthropocentric knowledge and therefore anthropomorphism (Epley et al., 2007), unless there is disconfirming information that inhibits the activation and application of such knowledge. For example, in an experiment by Nowak and Biocca (2001), they found that individuals interacting with an avatar of no image experienced higher social presence than those who interacted with an avatar represented by a low anthropomorphic image. In the latter condition, the lack of verisimilitude of the avatar seemed to have increased the saliency of the avatar's "nonhumanness," thereby discouraging anthropomorphism and compromising social presence.

Thus, when an OBT platform does not reveal its algorithmic process that may make its mechanistic nature salient, consumers should automatically apply their egocentric or anthropocentric knowledge related to impression formation and personalization to reason about the OBT processes, leading to anthropomorphism—attribution of human mental states to the OBT algorithm (Waytz, Morewedge, et al., 2010). This prediction is likely as suggested by existing research. In most HMC studies and in daily use of technologies, individuals do not have access to the algorithmic details of the technologies they interact with. If the prediction of the three-factor theory of anthropomorphism—individuals by default apply egocentric or anthropocentric knowledge to predict and explain a nonhuman agent—is correct, then anthropomorphism and its consequences (e.g., social presence and social responses) should be prevalently documented in HMC research.

So far, a plethora of research in HMC has observed the phenomenon of "media equation" or "computers are social actors" (CASA). That is, individuals tend to mindlessly apply social rules and expectations for humans when interacting with media technologies such as computers (Nass & Moon, 2000), robots (Lee et al., 2006), voice agents (Lee & Nass, 2005), and chatbots (Liu & Sundar, 2018). For example, individuals would rate a computer more positively, that is, more polite, when the computer asked about the performance of itself (as opposed to when it was another computer asking about its performance), as if they cared about how the former computer would feel about their evaluations (Reeves & Nass, 1996). A survey on how individuals talk to technical devices found that a majority of people verbally scold (78.2%) and curse (78.6%) their computer when it failed to comply with their intentions, as if these devices had the mental capacities to understand and communicate with the users (Luczak et al., 2003). Such a tendency is also manifested even when individuals interact with media technologies that are immaterial, non-anthropomorphic, such as websites (Kumar & Benbasat, 2002) and algorithms (Liu, 2020), when they seem to ignore the artificial, asocial nature of their machine interactants.

When technologies are used to track individuals' online behaviors, a context similar to OBT, research findings suggest that individuals by default respond to the machine gaze similarly to how they respond to the human gaze. In one study, participants were first instructed to download a Chrome browser extension that collected the URL, time, and duration of their visits to social media and other popular websites. When interviewed later, some participants spontaneously reported that they felt "being watched" as if "there's somebody behind me, trailing me" and "watching you, whatever you're doing" (Phelan et al., 2016, p. 5246). Another study even found a chilling effect of OBT such that participants reported that they intentionally changed their regular online behaviors when knowing their behavioral data were being collected (McDonald & Cranor, 2010). Such social responses to the tracking algorithms suggest that individuals had anthropomorphized the algorithms and experienced social presence as a result.

Taken together, we predict that when consumers are aware that their behaviors are tracked and analyzed by OBT algorithms but without knowing the exact algorithmic processes, by default, they will apply egocentric or anthropocentric knowledge (Epley et al., 2007). That is, they will use what they know about how themselves or prototypical humans process personal information to guide their interaction with the algorithms and respond as if they are gazed at by a person—experiencing social presence and being subject to the social influence of the OBT algorithm. This is the baseline condition in the present study.

2.3. Effects of algorithmic transparency: Revealing a mechanistic process

Although individuals may by apply their egocentric or anthropocentric knowledge to guide their perceptions of an unfamiliar machine, this may only be the case when they interact with a non-transparent machine and when they do not know the actual working mechanisms of the machine, as is the case in most CASA research (Nass & Moon, 2000). Per requirements of data use policies such as the California Consumer Privacy Act (CCPA), platforms that collect user data are expected to be transparent about *how* they analyze consumer data. With the algorithmic processes of OBT disclosed to consumers, the machine nature or its nonhumanness may become salient to consumers, which may discount the applicability of anthropocentric knowledge and thereby influence consumers' experiences with the platform and the recommendations personalized for them.

Admittedly, there are some apparent similarities between OBT algorithms and human minds as information systems. For example, OBT algorithms also gather information about others (i.e., tracking), generate person perceptions (i.e., consumer profiling), and act accordingly (i.e., predictive modeling and personalization). Nevertheless, there exists a fundamental difference between the two—machines do not form meaningful representations of personal data as humans do (Robinson, 2014; Rumelhart & McClelland, 1986). Below we discuss such differences between humans' cognitive processes and algorithmic processes of person perceptions.

In human-human interaction, the process of person perception is the formation of an *integrated* impression derived from the stimulus information provided (Anderson, 1995; Asch, 1946). As cognitive misers (Fiske & Taylor, 1984), individuals represent a target person by assessing the lower-order information of the target person against their existing knowledge structure, that is, their mental representations of social categories or dimensions, such as social roles, social groups, and personalities (Brewer, 1988). Individuals then use the integrated, higher-order representation of the target person in terms of certain social categories or dimensions to guide their future interaction with them (Carlston, 1980; Lingle, 1983). For example, if someone has inferred that the target person is extroverted based on the target's online behaviors, then they can predict that the target person may prefer to hang out with friends than staying home alone and may then invite the target person to their party.

This is not the case for many OBT algorithms that do not form meaningful higher-order representations of the consumers. Specifically, algorithms learn about the relationships between (certain combinations of) the lower-order features of consumer behaviors (e.g., clicks, viewing history) and the features of recommendation items (e.g., messages, ads, products) to maximize targeting effectiveness (e.g., click-through rate, ratings) (Ricci et al., 2015). The learning outcomes in this case, such as the algorithms' representations of consumer characteristics, are often uninterpretable to consumers and even domain experts (Lipton, 2016). For instance, it is often unclear what the (combinations of) lower-order features of consumers' behavioral traces really mean and why they are indicative of preferences of certain items.

In sum, such algorithms lack cognitive similarity with humans, with cognitive similarity defined as using "the same or similar dimensions" as humans when "categoriz[ing] events, objects, concepts, etc.," which is the premise for developing mutual understanding between two communication parties (Triandis, 1960, p. 175). For the sake of convenience, we label such algorithms as "observer algorithms" because they simply "observe" consumer features but do not form judgments about consumers on meaningful dimensions.

As discussed previously, when platforms are non-transparent about their algorithmic processes used in OBT, consumers by default experience a high level of social presence as a result of anthropomorphism (e.g., McDonald & Cranor, 2010; Phelan et al., 2016). According to the three-factor theory of anthropomorphism (Epley et al., 2007), individuals anthropomorphize only when the egocentric or anthropocentric knowledge is accessible and applicable. When the "observer" algorithm's algorithmic process is disclosed to consumers in terms of how it simply analyzes consumers' behavioral traces without forming higher-order representations of consumers on meaningful dimensions, the cognitive *dissimilarity* between the observer algorithm and humans will become salient to consumers. The salience of such *dissimilarity* may thereby discount the applicability of consumers' knowledge about how the self or a prototypical human forming impressions and making social predictions in their interaction with the observer algorithm. As such, consumers are less likely to anthropomorphize the OBT algorithm's gaze and are expected to experience less social presence as a result of the disclosure.

In addition, theories and research from the perspective of symbolic interactionism (Blumer, 1969; Mead, 1934) also suggest that anthropomorphism may be inhibited due to the paucity of shared meaning between human consumers and an observer algorithm. Specifically, when an observer algorithm represents consumers on dimensions unintelligible to humans, consumers can hardly share the meaning of the symbols used by the algorithm. Even though consumers are technically gazed at when tracked by an observer algorithm, its presence does not subject consumers to the same kind of interpretation that happens when they are gazed at by a person or any other entities that interpret them along dimensions meaningful to humans.

Based on symbolic interactionism, Blascovich (2002) proposed a now widely supported model of social influence in virtual environments that presumes shared meaning as the basis for social presence and social influence. Premised on this assumption, this model then predicts that people will be more influenced by virtual representations of humans that are indicative of human agency (e.g., being controlled by a human or showing high behavioral realism) than those that indicate machine agency (e.g., being controlled by a computer or showing low behavioral realism), because the latter implies less shared meaning with humans (e.g., Guadagno et al., 2007).

In an experiment that extends Blascovich's (2002) model of social influence to the context of human-AI interaction, participants interacted with an AI system that performed classification tasks (e.g., judging whether a news story is fake or not) by either following human-made rules (i.e., human-agency AI) or following machine-learned rules (i.e., machine-agency AI) (Liu, 2020). Participants reported more social presence with the human-agency AI than with the machine-agency AI in that the former was presumed to have more shared meanings with human users (Liu, 2020).

In light of theories and research in human communication with artificial agents discussed above, we predict that transparency of an OBT algorithm of low cognitive similarity to humans (i.e., the observer algorithm) will inhibit anthropomorphism and lead consumers to experience less social presence.

H1. Compared with no algorithmic transparency, transparency of the observer algorithm induces less social presence.

Individuals also differ from each other in their level of dispositional tendency to anthropomorphize nonhuman entities (Sundar, 2004; Waytz, Cacioppo, & Epley, 2010). Specifically, individuals with high anthropomorphism tendency are defaulted to see objects through an anthropomorphic lens and treat machines like people. Therefore, they are more likely to neglect the apparent differences between the observer algorithms and humans' mental processes in social information processing and may attend more to the similarities between them. Hence, we hypothesize that the negative effect of algorithmic transparency of the observer algorithm on social presence will be more prominent for individuals with lower anthropomorphism tendency.

H2. Anthropomorphism tendency moderates the effect of transparency of the observer algorithm (vs. no transparency) on social presence, such that the effect is more prominent for individuals with lower anthropomorphism tendency.

2.4. Social influence of OBT algorithms via social presence

According to Blascovich's threshold model of social influence (2002), social influence only occurs when individuals experience social presence. By influencing consumers' anthropomorphism and social presence, transparency of the observer algorithm may have downstream effects on OBT effectiveness in terms of consumers' perceptions of the personalization service, the recommendations, and the target products. Previous studies have linked anthropomorphism and social presence to positive attitudes and behavioral outcomes in general. For example, research has found that computers with anthropomorphic interfaces are perceived as more intelligent and more engaging for users (Koda & Maes, 1996), elicit more attention (Nass et al., 1995) and liking (Kozak et al., 2006), and are perceived as more credible (Burgoon et al., 2000).

In the context of e-commerce and marketing, empirical research has found that social presence induced by media technologies plays a significant role in enhancing message processing and persuasion (e.g., Skalski & Tamborini, 2007) and consumer experience (e.g., Choi et al., 2011; Verhagen et al., 2014). For example, an anthropomorphic design of e-commerce websites was found to enhance consumers' trust in the site via increased social presence (Cyr et al., 2009). Likewise, social presence induced by a personalizing virtual customer service agent was found to enhance users' satisfaction with the service agent (Verhagen et al., 2014). Choi et al. (2011) further found that social presence induced by a recommender system using collaborative filtering targeting increased individuals' trust in the recommender system and use intention.

In the case of algorithm-driven OBT, since transparency of the observer algorithm that lacks cognitive similarity with humans may inhibit consumers' anthropomorphism, consumers may not feel that they are interacting with an intelligent being (i.e., low social presence) who can understand them sufficiently to choose the right ads of products that they like. As a result, consumers may perceive the ads chosen by the OBT algorithm as less personalized for them and indicative of who they are (cf. Summers et al., 2016).

In addition to facilitating consumers' positive attitude toward and trust in the technology they interact with, anthropomorphism and social presence are found to have a positive influence on persuasion outcomes in the context of e-commerce and marketing. For example, anthropomorphizing a brand's Facebook fan page was found to improve the perceived brand's quality and strengthen the relationship between the brand and consumers by eliciting social presence (Kim et al., 2020). In the context of online shopping, anthropomorphism of service chatbots (Han, 2021), disembodied conversational agents (Kuosmanen, 2020), and websites (Wölfl et al., 2019), has been found to increase the level of social presence consumers experienced and thereby positively affect their purchase intentions and related behavioral outcomes.

Thus, we predict that transparency of the observer algorithm, compared with no transparency, will compromise consumers' perceived personalization and OBT effectiveness because it induces less social presence. These indirect effects via social presence should be moderated by individuals' anthropomorphism tendency, as previously discussed.

H3. Compared with no transparency, transparency of the observer algorithm induces lower a) perceived personalization, b) attitude to the advertisements, c) attitude to the brands, and d) purchase intention via social presence, with the indirect effects more prominent for individuals with low anthropomorphism tendency.

2.5. Testing a corollary: Effects of a "judge" algorithm

Predictions in H1–3 are based on the theoretical arguments that suggests when an OBT algorithm that does not form meaningful representations of consumers, the disclosure of its nature will discount the applicability of consumers' anthropocentric knowledge and thereby decrease social presence and social influence during HMC. A corollary of this argument follows as such, when an OBT algorithm involves meaningful representations of consumers and therefore a humanlike process of personalization, algorithmic transparency in this case will remedy the loss of social presence in HMC. The current study proposes to test this corollary to further examine the validity of the theoretical arguments that undergird the main hypotheses.

One prominent example of algorithms that represent consumers on meaningful dimensions is personality-based targeting (see Tkalcic & Chen, 2015). Recently, platforms have started capitalizing on the predictive power of personality inferences in modeling consumer behaviors (e.g., IBM Watson) by using algorithms that can infer users' personalities from their digital footprints (see Kosinski, 2019). OBT platforms can then factor into consumers' personalities when building predictive models for more accurate targeting.

Personalities are informative constructs that characterize "an individual's enduring and distinctive patterns of experience and behavior" (Cervone & Pervin, 2019, p. 4), which serve as a simple, cognitively economic, and often-used framework in representing and predicting other's behaviors during interpersonal interactions (Cervone & Pervin, 2019). For instance, research has found that individuals easily form their impressions of others along personality dimensions such as the big five traits (Uleman & Saribay, 2012).

As such, algorithms used in personality-based targeting are different from the observer algorithms such that they not only *observe* consumers' online behaviors but also *judge* them along evaluative dimensions that are meaningful to human consumers. Again, for the sake of convenience, we label such algorithms as "judge" algorithms. Judge algorithms share more cognitive similarity with humans as they both use personalities as dimensions to categorize people (Triandis, 1960). Such cognitive similarity between the algorithms and humans might serve as an anthropomorphic cue that renders anthropocentric knowledge accessible and applicable during HMC and induce social presence as a result (Epley et al., 2007). Thus, should the theoretical premises undergirding H1–3 hold, transparency of a personality-based judge algorithm should induce similar, or even higher levels of social presence and social influence, as compared with the non-transparent, default condition, due to its introduction of an additional anthropomorphic cue. Thus, we raise the following research questions to explore the effects of transparency of a judge algorithm relative to no disclosure on consumers' experience and OBT effectiveness.

RQ1. Compared with no transparency, does transparency of the judge algorithm induce different levels of social presence, with the effect moderated by anthropomorphism tendency?

RQ2. Compared with no transparency, does transparency of the judge algorithm influence a) perceived personalization, b) attitude to the advertisements, c) attitude to the brands, and d) purchase intention via social presence, with the indirect effects moderated by anthropomorphism tendency?

3. Method

We conducted a one-factor, three-level online experiment where we manipulated transparency of *how* consumer data were analyzed in OBT (i.e., no transparency vs. transparency of an observer algorithm vs. transparency of a judge algorithm). The study was approved by the Institutional Review Board in the pertinent institution before data collection (approval number: STUDY00013425).

3.1. Sample

From the Amazon Mechanical Turk (mTurk), we recruited 227 participants who were located in the United States and had a good survey-taking reputation (i.e., with 50 or more approved Human Intelligence Tasks) to ensure data quality.

We eliminated the data of participants who failed the attention check implemented in the questionnaire and those who did not believe that their behaviors were tracked for personalization, and the data of one participant with missing values on focal variables. The final dataset retains data of 209 participants, including 103 males (49%), 105 females (50%), and one indicating their gender as "Other." Participants' age ranged from 19 to 72 years old ($M = 39.67$, $SD = 12.71$). Among the 209 participants, 146 (70%) self-reported as Caucasian, 29 (14%) as Asian, nine (4%) as African American, seven (3%) as Hispanic/Latino, four (2%) as Native American, ten (5%) as multiracial, and four (2%) as "Other." More than half reported having a bachelor's degree or higher (64%) and household income of $50,000 or above (59%).

3.2. Overview of the procedure

After clicking the URL link to this study released on mTurk, participants were directed to a Qualtrics questionnaire. On the questionnaire, participants first read an informed consent form, in which the purpose and procedure of the study, potential benefits and risks, participants' rights, and the contact information of the principal investigator were provided. Specifically, participants were told that they were recruited to test the beta version of a browser extension, "Ads for you," which employed up-to-date machine learning algorithms to select personally relevant and pleasant ads for users. In fact, no machine learning algorithms were used and all materials were arranged by the researchers.

Because we did not use machine learning algorithms and therefore deception was involved, in the consent form we added "As part of the research, we may mislead you or we may not tell you everything about the purpose of the research or research procedures. At the conclusion of the study, we will provide you with further information." Only those who clicked "I agree to participate" proceeded to the rest of the study. After consenting to participate, participants first answered questions measuring their individual differences and then were directed to the "Ads for you" website (created using *Wix*. com, a website builder) where the three different experimental manipulations were executed.

"Ads for you" purportedly tracked participants' activities on it and then selected personalized ads for them based on its analysis of their activities. In reality, participants were neither tracked nor analyzed, and the ads finally displayed to them were not personalized but determined by the researchers beforehand.

To enhance the internal and external validity of the study, we employed stimulus sampling (Wells & Windschitl, 1999) by creating four different versions of ads under each experimental condition, resulting in a total of 12 versions of the "Ads for you" website. Participants were randomly directed to one of the 12 versions and experienced its ad personalization service by following instructions on the website.

On the last page of the website, participants were directed back to Qualtrics to complete the rest of the questionnaire, where they were asked about their experience with "Ads for you." At the end of the questionnaire, participants were debriefed about the purposes and procedure of the study, provided the opportunity to withdraw from the study by sending the unique code that Qualtrics.com randomly generated to the principal investigator, and thanked for their participation. Participants were compensated with $0.80 for their participation (15 min on average).

3.3. Stimuli: "Ads for you" website

We told participants that "Ads for you" was a browser extension that could personalize ads in their online environment such that "only relevant and great ads" would be displayed with "Ads for you" installed. The "Ads for you" website was purported to let participants try out its service of ad personalization and then decide whether to adopt it based on their user experience.

On the stimulus website, the first step was to purportedly collect behavioral data from participants. Therefore, on the homepage, we presented an interactive gallery as the banner and seven different ads under the banner so that participants could click around and feel as if they were generating behavioral data for "Ads for you" to process. The mission of "Ads for you" was introduced at the bottom of the homepage (see Fig. 1).

On the following four web pages (pages 2–5), participants were told that "Ads for you" wanted to learn more about them to personalize for

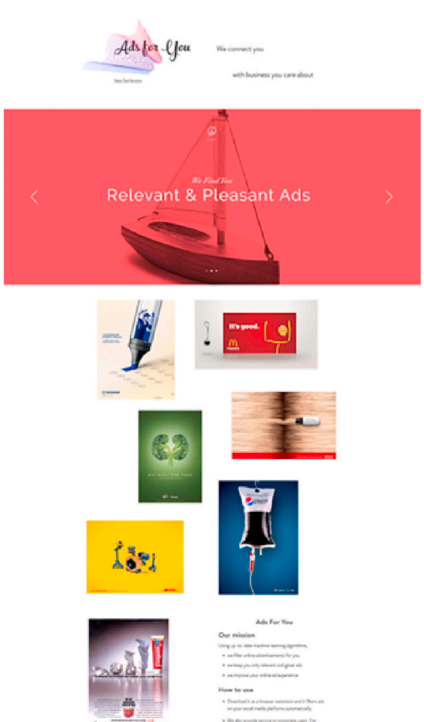

Fig. 1. The homepage of the "Ads for you" website.

them. Specifically, participants saw questions asking them to indicate their preferences for certain items on four different topics (i.e., movie genres, pets, social network sites, and school subjects) by dragging on a slider below each item (see Fig. 2).

3.3.1. Manipulation of OBT transparency

The second step was to implement the experimental manipulation, that is, to explain to participants how "Ads for you" analyzed their behavioral data it just collected. After participants had indicated their preferences for movie genres and so (pages 2–5), the next page presented them one of the three different descriptions of *how* "Ads for you" utilized their data to select personalized ads for them. To be noted, in all textual descriptions we avoided using anthropomorphic or mentalizing terms (e.g., "think," "believe") to describe the algorithm or the platform so as to prevent the participants from anthropomorphizing the stimuli due to the language cues, which is a procedure recommended and followed by Nass and Moon (2000). For example, when referring to "Ads for you," we used "the system" rather than humanized pronouns such as "I." Specifically, in the no-transparency condition, participants were simply informed that "The system is now selecting ads for you based on your earlier activities" (see Fig. 3).

In the observer-algorithm condition, participants were informed that "The system is now matching your earlier activities with certain ad characteristics" with a visual illustration showing the algorithm trying to establish an association between user actions (e.g., clicking, moving) and ad preferences (e.g., design, brand) (see Fig. 4).

In the judge-algorithm condition, participants saw "The system is assessing your personality (e.g., extraversion, neuroticism) based on your earlier activities" and then "The system is now matching your personality with certain ad characteristics," together with a visual illustration showing the algorithm trying to establish an association between profiled user personality (e.g., extraversion, neuroticism) and ad preferences (e.g., design, brand) (see Fig. 5).

3.3.2. Ads selection and presentation

The third step was to show participants a series of ads purported to be personalized for them based on their actions taken on the "Ads for you" website. On the following four web pages, participants saw 12 ads of four brands (i.e., three products of one brand on each page) purported to be personalized for them. To increase the perceived realness of the personalization, we used multiple (rather than just one) existing brands and products with broad appeal to the general population so that participants can find some of the ads personally relevant. The diversity of these ads also helped rule out potential confounding effects of product characteristics (e.g., search vs. experience, Xiao & Benbasat, 2007; or hedonic vs. utilitarian, Hassanein & Head, 2005) and brand images (e.g., masculine vs. feminine).

Specifically, we identified four categories of products/services of broad appeal, namely electronic products, books, home appliances, and tourism. For each category, we selected two brands that are similar to each other in their market positioning to increase the study's external validity. Specifically, we chose Google and Apple for electronic products, Penguin and Graywolf for books, KitchenAid and Ninja for home appliances, and Priceline and Expedia for tourism. For each brand, we generated ads for three different products (see Fig. 6). Notably, similar products were chosen for the brands in the same category to control for product-specific effects.

To ensure that the ads were not specifically appealing to female or male consumers and were not overly arousing, we pilot tested them with 61 participants recruited from mTurk who evaluated the ads of each brand on a seven-point Likert-type scale in terms of their genderedness ("To what extent do you think the ads were, 1 = for male consumers, 7 = for female consumers") and arousing level (index of three items 'When viewing these ads, to what extent do you feel "aroused," "excited," and "enthusiastic" 1 = not at all, and 7 = very much,' Mackay et al., 1978; Watson et al., 1988). Results show that ads of the eight

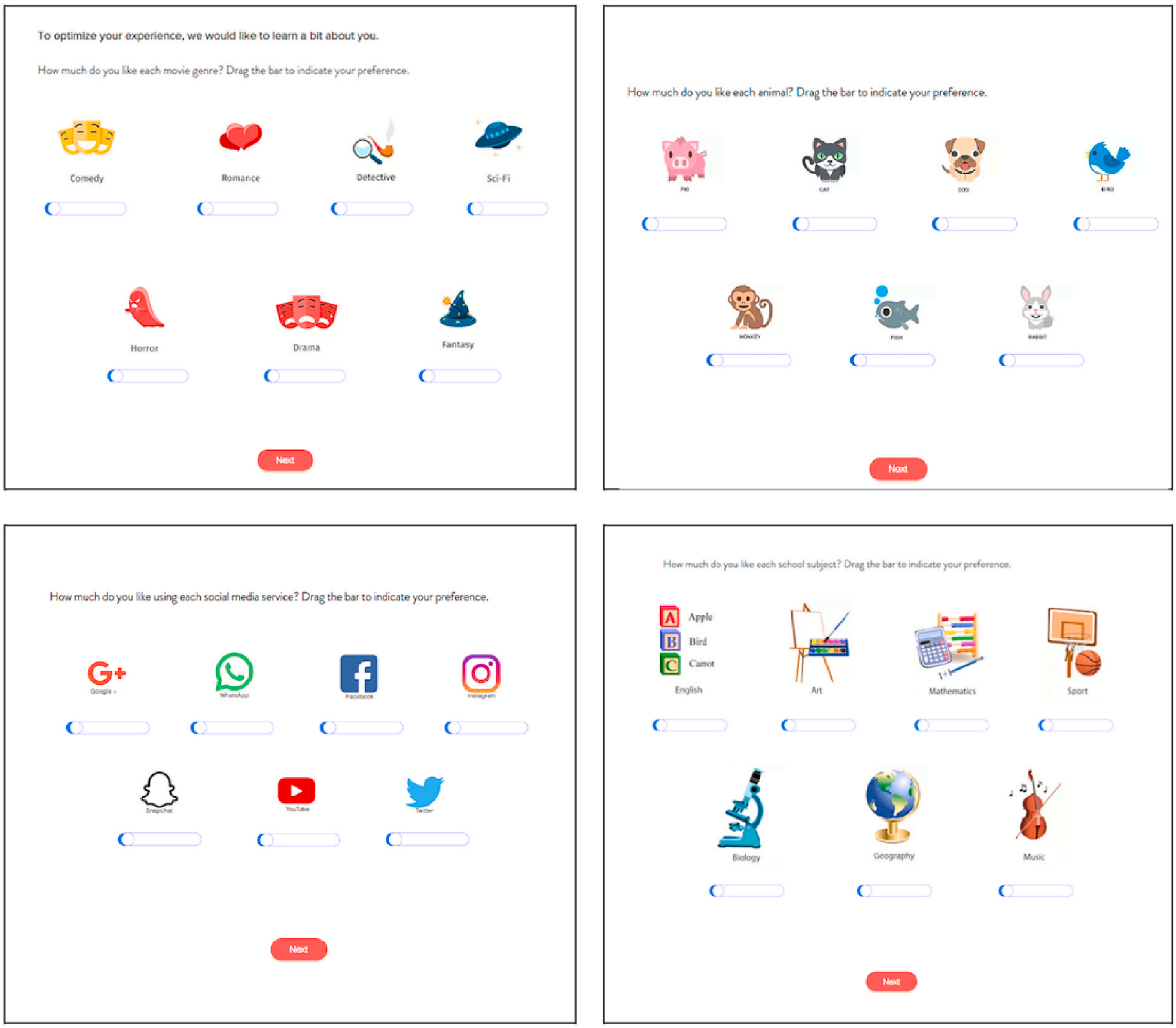

Fig. 2. Pages of "Ads for you" website asking for user input.

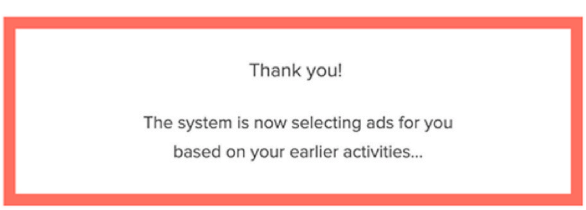

Fig. 3. Disclosure in the no-transparency condition.

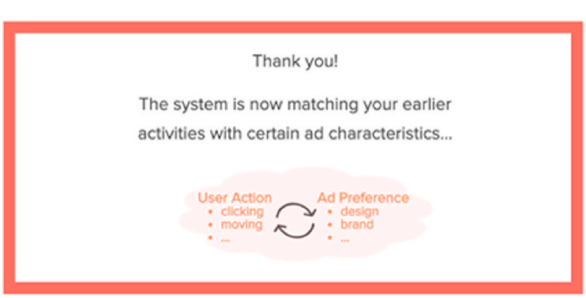

Fig. 4. Transparency of the observer algorithm.

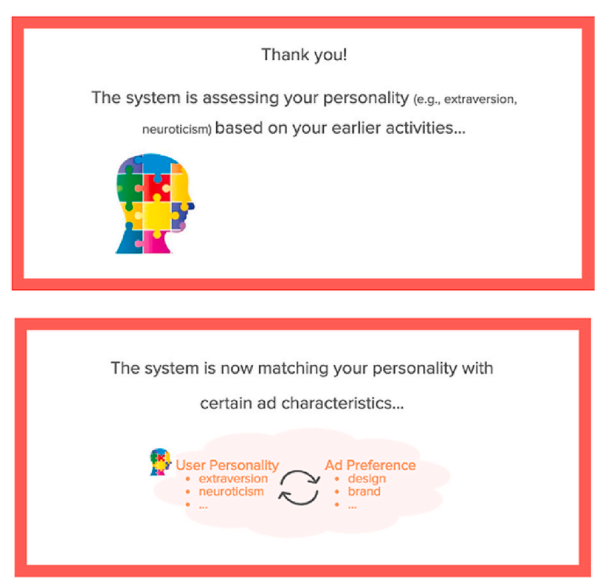

Fig. 5. Transparency of the judge algorithm.

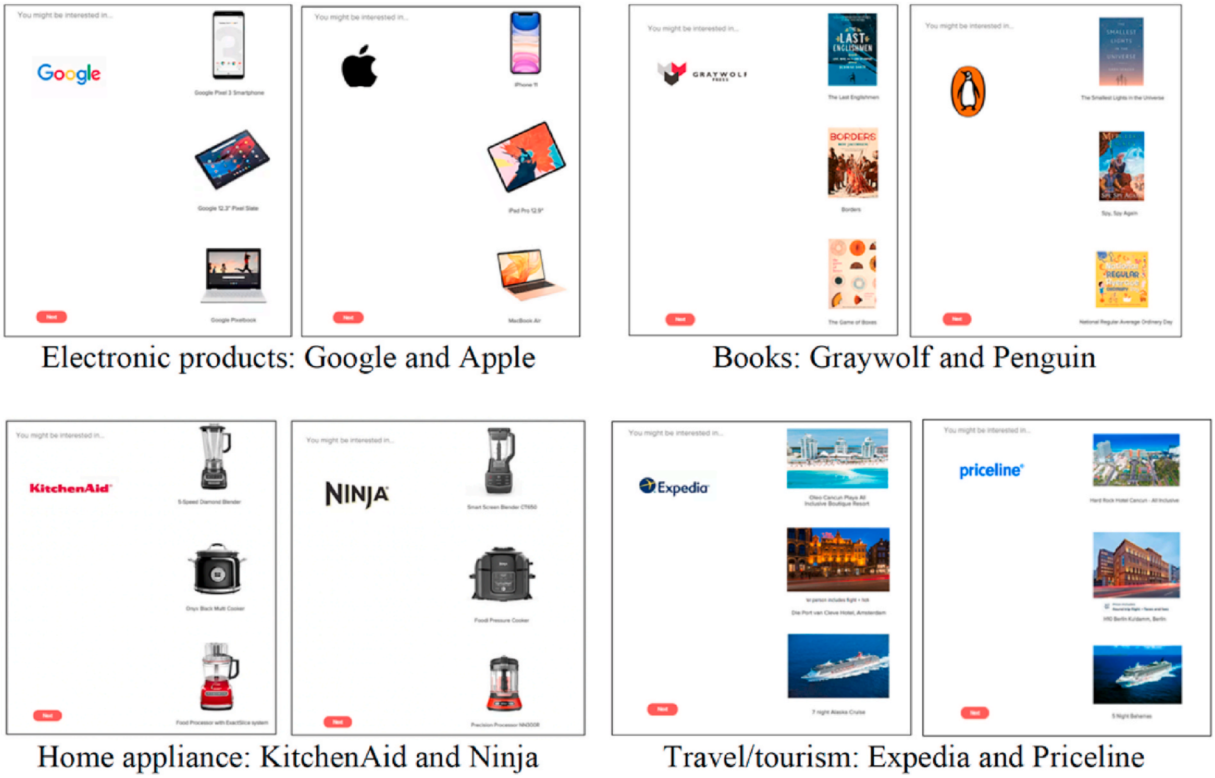

Fig. 6. Stimulus ads.

brands were all gender neutral (*Ms* $\sim$ 3.87 to 4.97, X_{GM} = 4.28, *SE* = 0.34) and moderately arousing (*Ms* $\sim$ 3.50 to 4.67, X_{GM} = 4.17, *SE* = 0.36).

As part of the stimulus sampling procedure, we divided ads of the eight brands into two sets, with each set containing four brands representing different categories. Within each set, to minimize order effects, we created two different orders of presentation, resulting in a total of four different versions of ads presentation under each experimental condition, namely A1 (KitchenAid-Expedia-Google-Graywolf), A2 (Graywolf-Google-Expedia-KitchenAid), B1 (Ninja-Priceline-Apple-Penguin), and B2 (Penguin-Apple-Priceline-Ninja). Participants were randomly assigned to see only one version of the ads.

3.4. Measurement

3.4.1. Covariates

The following individual differences were measured and later controlled for in data analyses because they have been found to influence individuals' attitudes toward OBT in advertising, including one's need for uniqueness (Ho et al., 2008), one's experience and concerns relevant to online behavioral advertising (OBA, Boerman et al., 2017), and age (Bittner & Shipper, 2014).

Need for uniqueness was measured with four items developed by Lynn and Harris (1997), such as "I prefer being different from other people," Cronbach's α = 0.92, *M* = 4.27, *SD* = 1.37, Skewness = −0.27, Kurtosis = −0.71.

Persuasion knowledge about OBA was measured with four items adapted from prior research (Ham, 2017), such as "I understand how a marketer shows tailored ads to me using OBA," Cronbach's α = 0.89, *M* = 4.61, *SD* = 1.32, Skewness = −0.88, Kurtosis = 0.77.

General attitude toward OBA was measured with four bipolar items that we created, namely, "Harmful–Beneficial," "Undesirable–Desirable," "Annoying–Pleasant," and "Risky–Safe," Cronbach's α = 0.95, *M* = 3.52, *SD* = 1.67, Skewness = 0.07, Kurtosis = −0.95.

Online ads exposure was measured by asking participants how often they saw ads when they "use search engines (e.g., Google, Bing, etc.)," "use social media platforms (e.g., Facebook)," and "surf the Internet in general," Cronbach's α = 0.83, *M* = 5.72, *SD* = 1.20, Skewness = −1.52, Kurtosis = 3.21.

General privacy concern was measured with three items adapted from Dolnicar and Jordaan (2007), such as "In general, I fear that my online behavior information might not be safe while stored," Cronbach's α = 0.94, *M* = 5.47, *SD* = 1.23, Skewness = −0.1.03, Kurtosis = 1.62.

Age was measured by asking participants "How old are you (in years)?" *M* = 39.67, *SD* = 12.71, Skewness = 0.58, Kurtosis = −0.49.

3.4.2. Moderator

Anthropomorphism tendency was measured with items adapted from the anthropomorphism scale in Sundar (2004), which was developed to measure one's behavioral tendency to treat machines like persons—an implicit measure of individual differences in anthropomorphism. We did not use explicit measures of anthropomorphism such as the one developed by Waytz, Cacioppo, and colleagues (2010), because we did not want to sensitize our participants with items such as "to what extent does the average robot have consciousness" in the beginning of the study. The original scale developed by Sundar (2004) contains 12 items with each describing a behavior discussed in a series of experiments reported in Reeves and Nass (1996) and asking participants to what extent they agree that they would engage in such a behavior. Because the original scale was effort-consuming (12 items, 239 words) and we did not want to exhaust participants before they interacted with the stimulus website, we selected three items from the original scale that are most realistic given today's technology. We ended up dropping the item 'I will say "thank you" or "well done" to the computer after it performs a complicated job nicely,' because including it lowered the overall reliability (Cronbach's α = .66). The final index was created by averaging scores of two items, 'If I am in a hurry to have a computer process a job, I will say "come on, come on" to the computer' and "If the computer does not perform the function I ask, I will curse it," Cronbach's α = 0.70, *M* = 4.08, *SD* = 1.56, Skewness = −0.23, Kurtosis = −0.72.

3.4.3. Mediator

Social presence was measured with seven items adapted from past research (Harms & Biocca, 2004; Lee et al., 2006; Liu, 2020), such as 'When interacting with "Ads for you," I felt as if I was interacting with an intelligent being,' Cronbach's α = 0.94, *M* = 3.12, *SD* = 1.56, Skewness = 0.30, Kurtosis = −0.76.

3.4.4. Dependent variables

Perceived personalization was measured with three items adapted from previous work (Dolnicar & Jordaan, 2007; Ham, 2017), such as 'How much do you feel that "Ads for you" made recommendations that matched your needs,' Cronbach's α = 0.96, *M* = 3.98, *SD* = 1.73, Skewness = −0.32, Kurtosis = −1.06.

Attitude to the ads (A_{ad}) was measured by asking participants to answer "How do you feel about the ads the system chose?" on five bipolar items adapted from existing research (El Hazzouri et al., 2019; Yoo & Lee, 2016), such as "Bad–Good," Cronbach's α = 0.96, *M* = 4.49, *SD* = 1.46, Skewness = −0.60, Kurtosis = 0.07.

Attitude to the brands (A_{brand}) was measured with the same bipolar scale as A_{ad}, with "brands" as the evaluation target in the question stem, Cronbach's α = 0.97, *M* = 4.91, *SD* = 1.32, Skewness = −0.57, Kurtosis = 0.39.

Purchase intention (PI) was measured with a four-item bipolar scale adapted from existing research (Li et al., 2002). Participants were asked to answer the question, "In general, how likely are you to purchase the items in the ads?" by rating on four items including "Unlikely–Likely," Cronbach's α = 0.97, *M* = 3.47, *SD* = 1.78, Skewness = 0.20, Kurtosis = −1.05.

Bivariate correlations among the outcome variables are presented in Table 1.

4. Results

4.1. Effects of transparency and anthropomorphism on social presence

To examine the effect of disclosing two different algorithmic processes and the moderating effect of anthropomorphism tendency on social presence (H1, H2 and RQ1), we used Model 1 in the PROCESS Macro in SPSS (Hayes, 2018) instead of other approaches (e.g., ANCOVA) for two reasons. First, it allows for comparisons between any experimental condition with a specified reference condition while statistically controlling for other experimental conditions, a procedure recommended in Hayes and Preacher (2014) when testing effects of a multicategorical independent variable (IV). Second, it computes conditional effects of IV when a continuous moderator (i.e., anthropomorphism tendency) takes different values. The present study reported unstandardized coefficients of the IV with anthropomorphism tendency taking values of its 16th, 50th, and 84th percentiles, referred to as low, medium, and high level respectively hereafter.

In Model 1, transparency was specified as the IV with the no-transparency condition as the reference condition, anthropomorphism tendency as the moderator, and social presence as the dependent variable (DV), with 5000 samples of bootstrapping requested with 95% Confidence Intervals (CI). The overall model was significant, $R^2 = 0.34$, $F(11, 197) = 9.06$, $p < .001$.

In support of H2, transparency of the observer algorithm (vs. no transparency) and anthropomorphism tendency had a significant interaction effect on social presence, *B* = 0.34, *SE* = 0.15, *p* = .020, 95% CI [0.05, 0.63] (see Fig. 7). Specifically, only among participants with low anthropomorphism tendency, transparency of the observer algorithm's algorithmic process (vs. no transparency) significantly lowered social presence, *B* = −1.06, *SE* = 0.37, *p* = .005, 95% CI [-1.79, −0.32]. For participants with a medium or high level of anthropomorphism tendency, transparency of the observer algorithm had no significant effect on social presence. H1 was not supported.

In response to RQ1, transparency of the judge algorithm (vs. no transparency) had no significant effect on social presence regardless of one's anthropomorphism tendency (low: *B* = −0.46, *SE* = 0.37, *p* = .222, 95% CI [-1.19, 0.28]; medium: *B* = −0.20, *SE* = 0.22, *p* = .379, 95% CI [-0.64, 0.24]; high: *B* = −0.003, *SE* = 0.31, *p* = .991, 95% CI [-0.61, 0.60]; interaction term: *B* = 0.13, *SE* = 0.14, *p* = .372, 95% CI [-0.16, 0.41]).

4.2. Indirect effects of transparency and anthropomorphism via social presence

To examine the indirect effects of transparency of different OBT algorithms on the ultimate DVs via social presence (H3 and RQ2), we employed Model 7 in the PROCESS Macro (i.e., first-stage moderated mediation) in SPSS (Hayes, 2018; see Fig. 8).

In support of H3, we found the indirect effects of transparency of the observer algorithm on all outcome variables via social presence were moderated by anthropomorphism tendency, whereas the indirect effects of transparency of the judge algorithm were not significant regardless of participants' anthropomorphism tendency (see Table 2).

Specifically, only among participants with low anthropomorphism tendency, transparency of the observer algorithm had negative effects on perceived personalization and OBT effectiveness via reducing social presence (see Table 3). For participants with a medium or high level of anthropomorphism tendency, such indirect effects were not significant.

4.3. Summary of findings

In sum, contrasts were conducted between the condition of the observer algorithm and the no-transparency condition and between the condition of the judge algorithm and the no-transparency condition, on social presence that consumers experienced and social influence of OBT, which included a) perceived personalization, b) attitude to the ads, c) attitude to the brands, and d) purchase intention. As hypothesized, individuals' anthropomorphism tendency moderated the effects of the observer algorithm such that it led to lower social presence only for

Table 1
Correlations among outcome variables.

	M	*SD*	1	2	3	4	5
1. Social presence	3.12	1.56	–				
2. Perceived personalization	3.98	1.73	.61***	–			
3. Attitude to ads	4.49	1.46	.44***	.73***	–		
4. Attitude to brands	4.91	1.32	.39***	.58***	.79***	–	
5. Purchase intention	3.47	1.78	.56***	.71***	.70***	.65***	–

Note. ***$p < .001$.

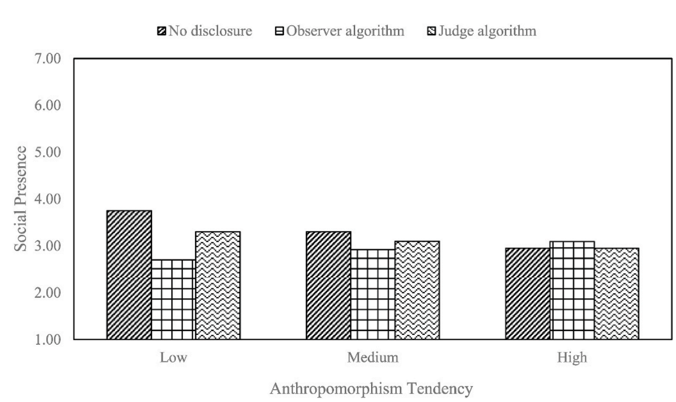

Fig. 7. Effects of algorithmic transparency on social presence contingent on anthropomorphism tendency.

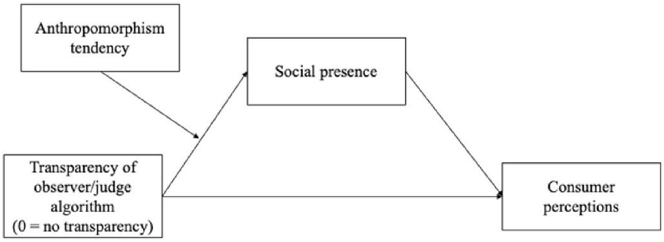

Fig. 8. Conceptual model of Model 7 in PROCESS Macro.

Table 2
Moderated mediation index for indirect effects of the algorithmic transparency via social presence.

	Observer algorithm			Judge algorithm		
	Index	Boot*SE*	95% CI	Index	Boot*SE*	95% CI
Perceived personalization	.18	.08	[.03, .36]	.07	.09	[-.10, .24]
A_{ad}	.07	.05	[.004, .18]	.03	.04	[-.04, .11]
A_{brand}	.05	.04	[.0004, .14]	.02	.03	[-.03, .08]
Purchase intention	.12	.06	[.02, .25]	.05	.06	[-.07, .16]

Note. The reference group was the no-transparency condition; the moderator was anthropocentrism tendency.

Table 3
Indirect effects of algorithmic transparency via social presence on outcome variables among participants with low anthropomorphism tendency.

	Observer algorithm			Judge algorithm		
	B	Boot*SE*	95% CI	*B*	Boot*SE*	95% CI
Perceived personalization	-.56	.22	[-1.02, −.18]	-.24	.22	[-.68, .19]
A_{ad}	-.21	.13	[-.52, −.02]	-.09	.10	[-.33, .06]
A_{brand}	-.17	.10	[-.40, −.01]	-.07	.08	[-.25, .05]
Purchase intention	-.37	.16	[-.71, −.11]	-.16	.15	[-.46, .13]

Note. The reference group was the no-transparency condition.

participants with a low tendency of anthropomorphism, which further compromised consumers' evaluation of the personalization system and OBT effectiveness. The judge algorithm made no perceptual differences compared with the no-transparency condition, regardless of participants' dispositional anthropomorphism tendency. Additional exploratory analyses[1] suggest that the differences between the observer algorithm and the judge algorithm on social presence and other outcome variables were not significant, neither was the moderating effect of anthropomorphism tendency on their differences.

[1] Using the PROCESS Macro in SPSS (Hayes, 2018), we re-specified Model 1 and Model 7, in which transparency was specified as the IV with the observer algorithm condition as the reference condition while other set-ups remained the same as described in the manuscript. For Model 1, we found transparency of the judge algorithm (vs. observer algorithm) and anthropomorphism tendency had no significant interaction effect on social presence, $B = -0.21$, $SE = 0.15$, $p = .15$, 95% CI [-0.50, 0.07]. For Model 7, we did not find a significant indirect effect of transparency of the judge algorithm (vs. observer algorithm) via social presence on any outcome variable regardless of one's level of anthropomorphism tendency (i.e., all 95% CIs included 0).

5. Discussion

This study set out to understand consumers' experience when being gazed at (i.e., being seen and interpreted) by OBT algorithms, with a focus on examining the conditions under which machine gaze generated the greatest social influence and why. Findings suggest that the similarity between the algorithmic processes and humans' social information processing and one's anthropomorphism tendency are key to OBT algorithms' social influence on consumers. Findings have both theoretical and practical implications.

5.1. Theoretical implications

First, the current study addresses a previously under-investigated aspect of consumers' experience with OBT and the effectiveness of OBT, that is, the outcomes of being gazed at by an unfamiliar, alien entity—a machine (Varnali, 2021). Past OBT research has focused on the exchange among various players (e.g., advertisers, consumers, and platforms; Chen & Stallaert, 2014) within the framework of social contract or social exchange theory (see Varnali, 2021 for a review). However, it is not only the human agency exercised by these players that matters in OBT, so does the agency of machine learning algorithms. Granted by their learning capacity (Mittelstadt et al., 2016), OBT algorithms may form representations that are meaningless and uninterpretable to human beings, a black-box issue commonly seen across various contexts where machine learning AI is deployed (Lipton, 2016).

Without shared meaning with humans, OBT algorithms can be conceived as alien beings that speak languages that humans do not understand. Being gazed at by an alien is such a critical aspect in consumers' experience in OBT. Although past research suggests that consumers feel social presence when tracked by algorithms (Phelan et al., 2016) and treat ads personalized for them by the algorithms as meaningful and indicative of who they are (Summers et al., 2016), it is probably the case only when the consumers are unaware of the algorithmic processes of OBT, as results in this study suggest. When the difference between an algorithm and humans' cognitive processing is made salient to consumers, interaction with the algorithm does not lead to as much social presence and social influence, because consumers may find the personalization as based on inscrutable self-images constructed by an alien entity.

Second, our findings suggest boundary conditions for the theory of media equation (Nass & Moon, 2000) and contribute to the theoretical understanding of the processes and outcomes of HMC. While the theory of media equation and the research following the CASA paradigm suggest that individuals tend to treat computers like persons, findings in the present study suggest that we treat computers like persons only when we *do not* have sufficient knowledge about their algorithms. As our results show, the highest level of social presence and social influence occurred when participants were unaware of *how* their behavioral data were analyzed for personalization. Under this circumstance, consumers know about the *existence* of OBT but not its algorithmic process. Thus, the alien nature of the OBT algorithm is not salient to consumers, which is the case in most CASA research where researchers disguise the nature of the machines by embedding anthropomorphic cues (e.g., identity, personality) in their interfaces or behaviors (Nass & Moon, 2000). When the knowledge about the machines' algorithmic mechanisms is not available or accessible, it is not surprising that individuals anthropomorphize and use what they know about how humans interact with each other to guide their interaction with the machines (see Epley et al., 2007). When information about the technology's algorithm is made available, anthropomorphism may be inhibited should the algorithm bear little cognitive similarity to humans' conscious mental processes and states, as in the case of the observer algorithm; but anthropomorphism may still occur if the algorithm is humanlike, as in the case of the judge algorithm. Yet, the finding that only individuals with low anthropomorphism tendency experienced less social presence in response to the apparent "machine cue" suggests that anthropomorphism is a strong tendency during HMC.

Taken together, findings suggest that people treat intelligent machines as social actors when they do not know the machines' distinctive algorithmic characteristics; when such knowledge is available and accessible, processes and outcomes of HMC depend on the nature of the algorithms. This explanation is also consistent with a recent theoretical perspective that suggests that media equation only applies at the initial stage of humans' interaction with media technologies; as users' experience with and knowledge about the specific media technologies that they interact with accrue over time, users will develop and apply unique, technology-specific scripts during HMC (Gambino et al., 2020).

Third, the current study goes beyond the mainstream HMC research that focuses on machines' performance and its effects, but focuses on a relatively understudied, albeit important aspect—its algorithmic process (Xiao & Benbasat, 2007). As such, it expands the scope of social cues of technologies that have been examined in HMC research, which are mainly morphic and behavioral cues (Xu & Liao, 2020). With the increasing application of algorithms across various contexts, HMC is not limited to interacting with embodied entities but could be ambient and distributed. The algorithmic aspects of a machine, such as characteristics of its "cognitive" structure and process, could also shape individuals' experience and relationship with it, as found in our study.

Fourth, findings in this study also illuminate how the effectance motivation and the cognitive factor—elicited agent knowledge—function jointly in shaping individuals' experience of anthropomorphism. According to the three-factor theory of anthropomorphism (Epley et al., 2007), high uncertainty about an agent is expected to facilitate anthropomorphism, which then satisfies one's effectance motivation (Waytz, Morewedge, et al., 2010). In other words, if people have low uncertainty about an agent to start with, they will be less likely to anthropomorphize that agent. Since there was additional information about how the algorithms functioned in both conditions of algorithmic transparency, participants' uncertainty about the OBT processes was supposed to be reduced by the manipulations, which should have led to lower anthropomorphism as compared with the no-transparency condition. But as it turned out, transparency of the judge algorithm did not decrease participants' social presence significantly, which suggests that the cognitive factor—anthropocentric knowledge elicited by the judge algorithm's human likeness—might have triggered anthropomorphism despite the diminished motivation to reduce uncertainty. Nevertheless, the additional anthropomorphic cue in the judge algorithm also did not trigger higher anthropomorphism than the no-transparency condition, which might be explained by individuals' diminished motivation to reduce uncertainty in the transparency condition. That said, because we did not measure uncertainty in the current study, we offer these speculative implications for future research to explore how the motivational and cognitive factors work in concert in shaping individuals' anthropomorphism.

Fifth, this study found that only individuals with low tendency of anthropomorphism were affected by the disclosure of the observer algorithm, which has implications for understanding the processes and outcomes of HMC in general. As predicted, individuals with high anthropomorphism tendency reported similar levels of social presence regardless of the variations in the external stimuli. They seemed to have anthropocentric knowledge available and highly accessible chronically, and therefore had a low threshold for such knowledge to be activated. This may help explain and organize the mixed findings in extant HMC studies that found inconsistent effects of anthropomorphic cues in technologies on individuals' perceptions and behaviors. For example, some studies have found that anthroponomic cues decreased anthropomorphism and social presence (e.g., Kim & Sundar, 2012; Nowak & Biocca, 2003), whereas others found the opposite (e.g., Nowak & Biocca, 2001). The inconsistencies might be explained by the variances in participants' dispositional thresholds of activating anthropocentric knowledge across the samples and also by the differences in the levels of human likeness of the technological stimuli across studies. Given that the outcomes of HMC are jointly determined by both the personal and situational factors as suggested by the current study, future research may further explore the interaction effects of the individual differences in anthropomorphism and technological characteristics.

5.2. Practical implications

Our findings have practical implications for designing media platforms that use OBT to enhance user engagement and consumption. Platforms are facing an increasing pressure to disclose how they use consumers' behavioral data. However, representations of consumers' characteristics and preferences formed through machine learning are not always sensible to consumers, even to AI scientists and domain experts (Lipton, 2016). Such alien nature of many OBT algorithms (i.e., their cognitive dissimilarity to humans), as found in the current study, may degrade the meaningfulness of the exchange between consumers and platforms and compromise consumers' experience with the personalization service, the content of the ads, and the target brands and products.

Given the finding in this study that social presence promotes positive consumer attitudes and behavioral intention, designers of OBT platforms may be incentivized to work toward enhancing social presence by means such as describing their algorithms processes in anthropomorphic terms (as opposed to mechanistic terms). However, we argue that the disclosure should remain truthful to be ethical. Rather than designing anthropomorphic interfaces or simply using language that suggest humanlike mental states, OBT platforms should provide meaningful and truthful accounts for how consumers' behaviors are represented and how personalization is realized. For instance, designers of OBT platforms might consider using approaches such as Explainable AI (XAI), which provides explanations for an AI's output in natural language (Gunning, 2017), or using features in consumer profiles that are both meaningful and of high predictive power (e.g., Eslami et al., 2018), such as mood, so that consumers can easily make sense of the logic of the algorithm and feel the messages and items that the algorithm selects for them as more meaningful and relatable.

5.3. Limitations and future directions

The current study has several limitations which should be addressed in future work. First, no actual personalization algorithms were used and all participants received ads randomly assigned to them, rather than personalized for them, resulting in a moderate level of perceived personalization ($M = 3.98$, $SD = 1.72$). Past research suggests a curvilinear relationship between the level of personalization and consumers' attitudes. For example, consumers might perceive an OBT algorithm negatively when the ads are highly personalized (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015), in which case, disclosing about the "machine nature" of the OBT algorithm might help tune down social presence and temper the creepiness consumers perceive.

Second, the current study focused on the HMC aspect of OBT practices by conceptualizing OBT algorithms as machines that gaze at consumers. Although this narrow scope allowed us to delve deeper in exploring the psychological processes underlying the influence of OBT, practitioners should also consider other relevant mechanisms and contextual factors in the actual deployment of OBT algorithms.

5.4. Conclusion

In conclusion, findings in the current study suggest that when the algorithmic processes of OBT are not disclosed, consumers by default use an anthropocentric mental model to guide their experience. When the algorithmic processes are disclosed, consumers' experience with OBT and OBT effectiveness depend on the human likeness of the algorithms and their trait anthropomorphism tendency. Transparency of algorithms that do not form meaningful representations of consumers (i.e., algorithms of low human likeness) compromises consumers' attitudes toward the personalization service, the ads content, and the target brands and products, especially for those with low anthropomorphism tendency. Alternatively, transparency of algorithms that represent consumers on the same dimensions as in humans' impression formation (e.g., personality traits) retains meaningful consumer experience and does not hurt OBT effectiveness. OBT platforms could work toward enhancing social presence in their disclosure by providing meaningful and truthful accounts of how consumers are represented by their algorithms.

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Credit author statement

Bingjie Liu: Conceptualization, Methodology, Formal analysis, Writing-Original draft preparation, Responses to reviewers, Revision of the manuscript. Lewen Wei: Conceptualization, Methodology, Formal analysis, Writing-Original draft preparation, Responses to reviewers, Revision of the manuscript.

Declaration of competing interest

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