Artificial Intelligence and Consumer Behavior: A Review and Future Prospects

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Documenting how technological change impacts consumer behavior has been an important area of researcher interest dating to the early days of consumer and marketing research. In fact, a 1942 *Journal of Marketing* article authored by market research industry pioneer Arthur C. Nielsen describes initial attempts to record consumer responses to radio advertising using a panel approach. The first mention of technological innovation and consumer behavior in the *Journal of Consumer Research* dates to its second issue (Ostlund, 1974). So, whereas each generation of consumer researchers has grappled with how new technologies implicate contemporary practice and theory, it is becoming increasingly clear that the task for the next generation of scholars will be to better understand how humans interact with increasingly autonomous artificial agents that demonstrate high levels of market intelligence. The emergence of AI technology over the past several years has impacted consumers in nearly every industry. This chapter provides a brief historical overview of AI, describes the current state of the art in consumer research in AI and concludes with forecasts of key issues of research importance in the years to come.

Pioneering research in AI

One of the first researchers to raise the possibility of algorithmic advantage over human decision-making considered the case of clinical diagnoses in mental health contexts (Meehl, 1954). Meehl controversially proposed that clinicians' tendency to combine intuition and experience with other analytical inputs resulted in sub-optimal decision-making as compared to the potential of algorithmic and actuarial models in predicting patient outcomes. This prediction flew in the face of conventional thinking, yet Meehl persisted in this belief. Subsequent meta-analytic research has since shown his prediction is true in many cases, and the idea that an algorithm can outperform a human decision-maker is certainly not as controversial today as when first propounded nearly seventy years ago.

Algorithms continued to grow in potency and proliferated throughout the 1960's and 1970's as computer processing capacities enabled the development of evermore sophisticated algorithms. Coincident with these developments, a famous thought experiment was proposed by John Searle (1980). The "Chinese room" example argues for the absence of an AI mind no matter how intelligently a machine behaves. In this example, an AI is capable of speaking fluent Chinese so convincingly as to pass the Turing test (Turing & Haugeland, 1950) and persuade a human interlocutor that the AI is indeed human. The argument goes that such a machine would still not have a mind identical to a human mind, regardless of how well the AI performed or behaved indistinguishably from humans. The Chinese room example thus provides a refutation of what Searle called "strong AI", which is the claim that an AI can develop a perfect replica of a human mind that is identical to the human mind in every way. The strong AI position is contrasted with a "weak AI" viewpoint which represents the current state of the art. Weak AI can be programmed to perform specific functions over specifiable domains without a human-like mind. Thus, how consumers perceive weak AI as compared to human actors has provided a rich body of research across multiple consumer domains.

History of AI Research in Marketing

Early research in marketing related to algorithms dates to the emergence of the Internet in the mid 1990's. At this point, Internet search engine algorithms were developed to facilitate the location of specific web URLs. Thus, early research into algorithmic performance focused on the ability of these algorithms to locate URLs based on search terms (Bradlow & Schmittlein, 2000; Lawrence & Giles, 1998). Early Internet research predicted that the emergence of the Internet would pivot the way firms and the consumers interact in a new "computer-mediated environment" to exchange information and make decisions, spawning various marketing research questions and propositions in the dawn of a new digital age to come (Hoffman & Novak, 1996). Over 25 years later, the emergence of the Internet has indeed ignited the emergence of other ground-breaking technologies such as Internet of things (Hoffman & Novak, 2018), artificially intelligent robots in consumer domains (Huang & Rust 2018, Wirtz et al., 2018), and virtual reality and decentralized virtual worlds (Sherman & Craig, 2018).

AI in marketing mostly consists of a set of algorithms that are used to synthesize data with the goal of performing key business functions. These algorithms have grown increasingly sophisticated, encompassing natural language processing abilities, image and auditory pattern recognitions and neural deep learning computational capacities. The most advanced AI systems are capable of mimicking human sensory abilities while possessing large advantages in the ability to collect, store and process data. Still, these systems are "intelligent" in a narrow sense in that they are designed to perform specific, clearly delineated functions (i.e., domain specificity). For example, IBM developed an algorithm capable of defeating chess grandmaster Garry Kasparov in 1997. More recently, such domain-specific intelligence was extended to compete at Go, the most difficult human strategy game ever devised. In 2016, Google's AlphaGo won a series against Lee Sedol, who had achieved the highest-level mastery (9 dan ranking) and is widely considered the top Go player of his generation. However, the narrow intelligence enabling AlphaGo's victory would not carry over to other games with different rules (e.g., chess) thus revealing the limitations of domain-specific superhuman intelligence. In that sense, the general intelligence of humans is vastly superior to even the most advanced AI, and there is considerable debate about when (or if) AI may surpass human intelligence in a generalized, non-task oriented way. Much scientific and philosophical debate has surrounded the concept of a "technological singularity", the moment when a greater-than-human technological intelligence drives progress, thus wresting human autonomy and subordinating human ambition to a technological master (Vinge, 1993). Surveys of AI scientists suggest that many researchers believe such a singularity may occur by 2050. At present, algorithms and AI drive technology in literally every sector of society. Spanning news and entertainment, business, legal, medical, and government applications, algorithms effectively shape contemporary life to the extent some may argue these technologies effectively shape thought and behavior to a great degree already. Are humans losing control of progress? At present, the question is an open one, but there is no doubt as to the profound impact technology-based interactions have had on transforming society in general, and, the pace and flow of businesses more specifically. Academic research is beginning to crystalize around documenting negative and positive perceptions related to how interactions with AI change human experiences.

In the past decade of marketing scholarship, researchers have begun to examine these issues through a consumer lens (Puntoni et al., 2021). In the next section, we document the state of the art of consumer research involving AI-human interactions and divide the literature into two primary areas based on whether the reported effects are instantiations of consumers displaying a positive or negative response to encounters with AI.

Consumers are Averse to Algorithms

Algorithmic errors versus human errors. A seminal paper documenting consumer "algorithm aversion" was conducted by Dietvorst et al. (2015). This work documented that consumers prefer forecasts made by humans as opposed to forecasts made by algorithms, even when algorithms demonstrably perform better. This effect was explained by the finding that consumers more quickly lose confidence in algorithms when they make mistakes as compared to human forecasters. These findings suggest an asymmetry in how algorithmic errors and human errors are perceived by human actors. In a follow-up study, Dietvorst et al. (2018) found that the algorithm aversion phenomenon was attenuated when people were able to modify algorithms slightly with their own inputs. This study found that providing some degree of control over algorithmic calculations resulted in a greater willingness to accept the conclusions of algorithmic decision-making, even when individuals realize algorithmic decision-making is imperfect. Similarly, research by Palmeira and Spassova (2015) found across legal and medical decision-making contexts that algorithm aversion was reduced by a hybrid approach whereby algorithmic inputs were combined with the advice from a human expert. Their findings demonstrate a greater preference for a hybrid approach over either human expert or algorithm advice alone.

Consumers believe algorithmic offers are less unique. Other research has documented objections to the usage of AI in a medical decision-making context. Longoni et al. (2019) found that consumers derive less utility from medical AI as compared to interactions with human doctors. This research identified a uniqueness neglect process whereby consumers disfavor AI medical systems because they believe such systems are insensitive to individualized aspects of health care exclusive to the self. They found that this effect was stronger among consumers that viewed themselves as higher in perceived uniqueness. Research examining the automation of products and services found consumer distaste for the AI-administered offerings was driven by the degree to which the activity was a core part of consumer self-identity (Leung et al., 2018). In contexts like driving, cooking or fishing, where consumption requires the performance of non-trivial skills, automated experiences are enjoyed less among those who strongly associated the activities with their self identity. Similarly, research showed that in symbolic consumption contexts, such as getting a tattoo, consumers were averse to using AI due to the belief that AI offerings were less unique (Granulo, Fuchs, & Puntoni, 2020). Although this research did not examine AI directly, the findings suggest that improved convenience and efficiency achieved with AI are not always desirable for all consumers. Other research in a utilitarian decision context found that reminding consumers of the uniqueness of their own preferences attenuated their inclination for algorithmically derived recommendations as compared to human recommendations (Cian & Longoni, 2020).

Another guiding principle for algorithmic aversion is that consumers may view AI as stealing consumer autonomy (Wertenbroch et al., 2020). Autonomy is a human value, and, to the extent that AI systems replace, remove or retain power over consumer choices, some consumers will disavow this technological infringement over their decision-making sovereignty. Jorling et al. (2020) found that consumer enjoyment of positive outcomes was dampened in interactions with AI as compared to humans due to lower perceived control over the outcome.

Another domain where algorithms have become dominant in consumer markets relates to recommendation systems based on consumer preferences (Yeomans et al., 2019). Research has shown evidence for the algorithm aversion effect in the context of subjective humor whereby consumers prefer recommendations for jokes from humans as opposed to algorithms. This aversion could be overcome by informing people how the algorithms work, thereby alleviating suspicions of subjectivity or arbitrariness in evaluations (Yeomans et al., 2019). Other research has documented compensatory processes in interactions involving service robots (Mende et al., 2019). This research found that consumers experienced discomfort in these encounters that drove a bias toward selecting higher status goods and a greater desire to make choices that better satisfied social affiliation goals.

Consumers don't trust AI in emotional domains. Recent research by Cian and Longoni (2020) showed a relative consumer preference for algorithms in utilitarian decision-making as compared to hedonic decision contexts. When consumers held a hedonic goal, they were distrusting of AI due to the belief that algorithms are less competent recommenders when the goal of the task is to provide human enjoyment owing to the fact that consumers believe human recommenders are better able to capture human experience in the emotional domain. Related research examined perceptions of the automation of certain occupations, a phenomenon called "botsourcing" (Waytz & Norton, 2014). This research showed that people were less accepting of automation for jobs that required emotional skills as compared to cognitive skills due to the belief that humans were better suited to perform in jobs requiring understanding and exhibiting emotional responses.

Consumers are averse to AI as moral agents. Other research shows that humans are averse to the idea of AI making moral decisions. One emerging research context where AI morality is playing a role is with autonomous vehicles (Shariff et al., 2016). This research showed that consumers believe that autonomous AI technology in driverless cars needs to make moral decisions in order to function and are generally receptive to the technology. Research has shown that consumers believe it is more morally acceptable for a self-driving car to harm a pedestrian as compared to a human driver due to reduced perceptions that machines are moral agents and machines deflect human responsibility that would normally be ascribed to a human driver that harms pedestrians (Gill, 2020). However, consumers are hesitant to use technology that might sacrifice their own life in certain contexts. This hesitation may also interact with branding effects such that owners of costly luxury autonomous vehicles like Bentley or Mercedes-Benz might have different expectations about the autonomous vehicle trading off the owner's life as compared to non-luxury and more inexpensive branded vehicles. One interesting research application in this area is the moral machines project at MIT. This project has collected data from millions of respondents globally and asked what decisions an autonomous driving AI should make when the tradeoffs include the potential loss of human life (Awad et al., 2018). The results of this study show vast cultural differences in human life tradeoffs in relative preference towards saving youth over elderly, women over men, pets versus humans and those that are violating traffic laws, among a variety of other factors.

Outside of the driving domain, research by Bigman and Gray (2018) showed people were uncomfortable with AI making life and death decisions in legal and medical decision-making contexts. This effect was explained by reduced mind perceptions as compared to human decision-makers. The perceived inability for AI to process human morality leads to discomfort with consequential decisions being adjudicated by AI. Similarly, research by Huang and Chen (2019) in a prosociality context showed that people found stories of human rescue to be less inspiring when they involved robotic, as opposed to human agents. This effect was due to reduced perceptions of autonomy and resulted in lower willingness to donate to the prosocial organization when AI technology was used.

Other research by Bigman, Waytz, Alterovitz and Gray (2019) identified additional factors related to perceptions of AI that drove the extent to which AI was viewed as moral actors. Their research found that perceptions of how situationally aware the AI was determined the extent of moral blame for decisions that resulted in harmful consequences for humans. Another factor was the perceived capacity for harm. When AI and robotic technologies possess many human-like abilities, such as walking and talking, consumers tend to view these agents as more human-like and thus possessing a greater capacity to harm humans.

In an organizational hiring context, research by Newman, Fast and Harmon (2020) found that people felt that human resource decisions (promotions, terminations, hiring, etc.) were deemed less fair when stemming from algorithmic calculations as compared to decisions with identical outcomes resulting from human decision-makers. This effect was explained by the belief that algorithmic decision-making is inherently reductionist and thus failed to take into account key factors that may bolster one's case. Thus, algorithmic decisions are perceived as less fair in this domain as compared to human decisions.

Dishonesty toward robots. Additional research has shown that humans behave more unethically when interacting with AI representatives of companies as compared to human representatives (Kim, Lee, Kim, Kim, & Duhachek, 2021). This research asked consumers to list reasons for returning a product that they had purchased but had changed their mind about keeping. This study found that consumers were more likely to use a false rationale for returning a product (e.g., "it was defective") when interacting with AI as compared to humans due to reduced perceptions of guilt about being deceitful with AI as compared to lying to another person. The effects were not attributable to differences in perceptions of having the lie be detected across AI and human conditions.

The research presented thus far finds evidence for the existence of an algorithm aversion effect across a variety of domains. Moreover, this research points to multiple distinct mechanisms that each drive aversion in different contexts. A recent meta-analysis attempted to formalize the set of findings within the algorithm aversion literature and identified five distinct mechanisms driving algorithm aversion (Burton, Stein, & Jensen, 2018). One mechanism relates to differential expectations such that past failures are judged more harshly in algorithms as compared to past failures with humans (Dietvorst et al., 2015). A second mechanism relates to loss of control. For instance, Dietvorst, Simmons, and Massey (2018) found that allowing humans to modify algorithmic inputs only slightly and not in ways that materially impacted performance led to significant improvements in trust in algorithmic decision-making. A third mechanism relates to misaligned incentives wherein human decision-makers are not incentivized to rely on algorithmic decision-making. A fourth mechanism relates to perceived incompatibility whereby human users view algorithms as being rigidly inflexible and failing to conform to unique conditions within the decision environment. One means of overcoming this barrier would be to develop training aids that inform users as to the intuitions of the algorithmic model (Hafenbrädl et al., 2016). A final mechanism stems from differing definitions of rationality whereby human decision-makers sometimes fail to ascertain the guiding principles of algorithmic modeling. To view human decisions based on heuristic principles guided by a contextual factor, such as an emphasis on making decisions quickly, as sub-optimal or in response to imperfect information, fails to account for the decision environment in which consumers are embedded.

To summarize, consumers are more averse to algorithms when 1) they see algorithms make mistakes; 2) consumer desire customized or individualized interactions; 3) the interaction involves subjectivity and/or emotionality over objectivity and/or rationality; 4) the context involves AI making decisions with human moral implications. Research has demonstrated these effects in consumer, organizational, legal, medical and ethical decision-making domains. Despite the seemingly robust existence of human aversion to algorithms, their use across each of these domains has proliferated in recent years, indicating that there might be more to the story than a simple aversion-based account would allow. Along these lines, a stream of research has begun documenting conditions in which humans seem to favor decisions made by algorithms over identical decisions made by humans.

Consumers Appreciate Algorithms

In some instances, humans seem to appreciate algorithmic input more so than human input, a phenomenon known as algorithmic appreciation. Logg et al. (2019) reported that in many instances, humans show an increased affinity for algorithmic forecasting in contrast to the human-centric bias reported previously. Logg et al. (2019) note the wide and ever-expanding influence of algorithmic forecasting across consumer domains, including romantic matchmaking, product recommendations, legal advice, Internet search, music, dining, clothing and travel, to name but a few. This rapid growth suggests a different story than that identified by the literature documenting algorithm aversion. A key distinction between the algorithm aversion reported by Dietvorst et al. (2015) and the algorithm appreciation studies relates to the role of performance feedback. Logg et al. (2019) examine instances where consumers are not given negative performance feedback and thus demonstrate that in some neutral settings, consumers can be quite positively predisposed to algorithmic forecasts, even preferring them to human forecasts. Their research found that humans favored algorithmic advice in predicting business and geopolitical events, song popularity and romantic attraction.

Consumers disclose more to AI. One potential advantage algorithms hold over human actors relates to contexts where socially conscious emotions such as guilt, shame and embarrassment come into play. In many health, legal and business contexts, firms desire that consumers disclose sensitive personal information. This information often carries the potential for negative social judgment and stigma. Research by Kim, Li, Duhachek, Lee, and Garvey (2021) found that consumers were more willing to disclose sensitive information when the request came from an AI as opposed to a human agent. This effect is driven by consumer perceptions that AI is generally perceived to lack social and emotional capabilities (Gray et al., 2007; Waytz & Norton, 2014), and customers may perceive a less social risk of disclosing sensitive personal information to a service robot than a human service provider. This AI research extends an older survey research literature that examined respondent willingness to disclose information to computer-mediated interviewers as opposed to human interviewers (Nass & Moon, 2000). The fact that AI has increasingly human-like qualities cast doubt as to whether the survey research findings were still applicable in today's technological environment. Initial studies seem to confirm an AI-enhanced disclosure effect still predominates, although the ability of AI to record and store additional information for perpetuity raises questions as to whether or not a tipping point will be reached past which consumers will show a decreased willingness to share with AI.

Algorithms are competent, not warm. Research has shown that interpersonal perceptions of autonomous agents vary along two core dimensions: competence and warmth (Fiske, Cuddy & Glicke, 2007). One study in a chatbot sales context found that humans purchased less when it was revealed the sales agent was a chatbot because they perceived the agent to be less empathetic despite displaying objective advantages over human sales agents in the domain of objective knowledge (Luo et al., 2019). Research has shown that consumers believe AI are more competent than warm. Castelo et al. (2019) focus on identifying conditions under which consumers' algorithmic aversions can be overcome. Their research shows that consumers prefer algorithms for tasks that are more objective, defined as having quantifiable and measurable outcomes and demonstrated aversion to algorithms for subjective tasks, defined as tasks that are opinion-based or rely on intuition. They found that informing consumers that tasks naturally rated higher in subjectivity, such as choice of a romantic partner, were decisions best made by considering quantifiable dimensions of human personality led consumers to place more trust in algorithms to make such decisions. Conversely, informing consumers that such decisions are more intuitive and subjective reversed the preference for advice from algorithms to human experts. Additional research by Cian and Longoni (2020) documented a "word of machines" effect in contrast to the impact of word of mouth effects to compare the relative influence of AI recommendations as compared to recommendations from one's social network. This research found a relative bias toward AI recommendations in the domain of utilitarian products and services due to the belief that AI systems outperformed humans with respect to competence. In contrast, consumers showed a relative preference for human recommendations in hedonic domains where human advantages in warmth drove a greater belief in the accuracy of their recommendations.

Algorithmic errors are sometimes perceived less negatively. Another recent paper by Srinivasan and Sarial-Abi (2021) found that consumers respond less negatively to brand crises stemming from errors made by algorithms as compared to human errors, such as in the case where an algorithmic error produced product failures leading to safety issues with an automobile. This research found that differences in theory of mind led to less negative attributions resulting from brand failures involving algorithms as compared to humans due to the fact that human actions are driven by a higher perceived agency. The research found that consumers respond more positively when errors are repaired by technological means (as opposed to humans), thereby implicating the same theory of mind mechanism which connects human agency to the brand failure.

Recent research by Garvey, Kim and Duhachek (2021) provides a more nuanced account for the algorithm aversion-algorithm appreciation continuum by examining how deviations from expected outcomes produce varied perceptions of firms as a function of whether the interaction was with AI or human agents. This research found that for positive deviations from expectations, such as the case where a consumer is given an unexpectedly low price for a product or service, consumers viewed human agents more positively than AI agents. However, when the deviation was negative, such as in the case of an unexpectedly high price, consumers responded more negatively when the transaction was with a human as compared to an AI agent. The explanation for this effect related to differences in perceived intentionality such that humans were perceived to be have both more selfish and more charitable intentions in the case of negative and positive deviations, respectively. This research showed that consumer appreciation for algorithms is context-dependent, and human agents are preferred when positive outcomes obtain and AI agents make negative outcomes feel less negative than the same outcome delivered by human agents.

Algorithms versus humans through the lens of persuasion. One potentially valuable theoretical framework through which the aforementioned AI effects can be viewed is a persuasion framework. According to this framework, three independent sources of information conspire to determine the degree to which an individual is persuaded by a marketing advocacy. Thus, the current review discussing the degree to which consumers deem information and decision recommendations presented by AI as acceptable reflects the degree to which they were persuaded by the information presented. According to this framework, the degree of persuasion resulting from a message emerges from the conjunction of source factors (relevant AI or human recommender characteristics), message factors (the format and content of the recommendation or decision), and recipient factors (consumer characteristics, such as receptivity toward technology). Whenever these independent factors "match", greater persuasion occurs and we can expect consumers to find the decision or recommendation to be more accurate and their subsequent behavior to be more in line with the recommendation.

For instance, research by Kim and Duhachek (2020) examined compliance with health advocacies given by either AI technology or human medical doctors. This research identified a relevant source factor that drove perceptual differences between AI and human doctors related to construal level theory. AI were perceived to be low construal agents that lacked intentionality, whereas human doctors were perceived to be high construal agents. As such, messages that matched the construal level perceptions of the source resulted in greater persuasion and a more positive evaluation of the AI. Thus, messages from AI sources that focused on how to perform health-promoting behaviors such as applying sunscreen were more persuasive than messages that focused on why performing such behaviors was important.

In the context of the research we have reviewed, several potential sources and message matching conditions emerge. For instance, the research finding from the algorithm aversion paradigm that consumers distrust AI to make subjective decisions creates a potential match related to the objectivity of the decision or information presented to consumers. Thus, a message or decision presented as being based on subjective terms would be viewed negatively. In contrast, a task or decision framed as being based on objective information would be viewed more positively. Alternatively, a message or decision based on discussing sensitive information or with potentially embarrassing consequences should result in algorithmic appreciation relative to the same message being presented by a human.

Process Mechanisms Driving AI Effects in Consumer Research

This section reviews several broad streams of literature that relate to improving extant understanding of the underlying processes at play in guiding consumer interactions with AI. The goal of this section is to identify key psychological pathways that drive consumer response to AI and demonstrate how these processes mediate and moderate the effect of AI on important downstream consumer consequences. This section details five key process mechanisms in order of importance for the impact that they have had to date on the consumer literature.

Anthropomorphism. The tendency to humanize non-human entities (i.e., anthropomorphism) has been documented extensively in different realms of research, such as, psychoanalysis (Freud, 1927), animal studies (Darwin, 1872), and the study of religion (Hume 1757) in which humanization of non-human agents is a common phenomenon. For example, God is often depicted with human traits (or humans are said to reflect Godly traits) across many religions. The theory of anthropomorphism posits that such a chronic feature of human judgment can be explained by three antecedents (Epley et al., 2007). The first antecedent relates to the degree of knowledge about human behaviors (i.e., the basis) and how the knowledge extrapolates to explain the behavior of non-human targets. According to the theory, one's abundant (vs. limited) knowledge about human behavior leads to increased anthropomorphism whereas abundant (vs. limited) knowledge about the non-human target leads to decreased anthropomorphism. This antecedent often interplays with another anthropomorphism antecedent, namely an "effectance" motivation referring to the attributional desire to explain non-human agent's behavior using human behavioral terms. Human-centric attributions are generated readily and are done for the convenience they provide in interpreting ambiguous behaviors observed in non-human autonomous agents. Taken together, the two anthropomorphism antecedents could drive a consumer to more likely anthropomorphize interactive smart gadgets, such as, Alexa or Google Home, when the consumer has high (vs. low) motivation to explain non-human behavior through a human behavior lens (i.e., effectance need), and, has the ability to do so (i.e., level of knowledge about human and non-human agents).

One consequence of AI anthropomorphization could be the formation of consumer AI lay theories (i.e., ordinary people's naive attitude or set of beliefs about AI) which could be used by consumers in their judgments and decision making related to AI. The burgeoning literature on AI has identified a unique set of lay AI theories among consumers, including some fundamental perceptions such as AI's nonhuman-ness and lacking of emotions, goals, autonomy, and contextual understanding (Gray et al., 2007; Kim & Duhachek, 2020; Longoni et al., 2019). Other lay theories have been shown to impact downstream consequences in the contexts of marketing offers evaluations (Garvey et al., 2021), receiving services from humanoid robots (Mende et al., 2019), feelings about robots saving human lives in rescue missions (Huang & Chen, 2019), moral victimization of AI (Kim et al. 2022), and reactions to robots taking over human jobs (Jackson et al., 2020; Waytz & Norton, 2014).

The final antecedent of the anthropomorphism tendency relates to innate human needs for social belonging. Individuals may fulfill their desire to connect with other people by humanizing non-human entities to increase a sense of belongingness or purpose or to meet consumer needs for social affiliation. For this reason, socially excluded consumers (vs. not) exhibit stronger tendencies to anthropomorphize technologies (Epley et al., 2008) and more strongly favor anthropomorphized brands (Chen et al., 2017).

Previous marketing research on AI has shown that anthropomorphism can be implemented in a variety of ways to endow non-human agents with human traits. The most common form of anthropomorphism is to make a non-human agent human-like in its appearance. In the context of robot anthropomorphism, three physical factors were identified to influence the extent to which robots are perceived to be human-like: human-like face (e.g., presence or absence of human eyes, head shape etc.), human-like skin material (e.g., use of silicon versus metal), as well as the resemblance of humans anatomically (e.g., possess arms and legs) (Zhao et al., 2019). In fact, a rich database of commercial and industrial robots has been compiled and tested for the degree to which each robot captures human-like qualities along a range of dimensions (see ABOT database for more information at http://abotdatabase.info). The database has collected consumer perception data on over 250 existing robots. Alternatively, outside the realm of physical features, researchers have found that sometimes adding more socially nuanced human-like characteristics to AI (e.g., giving a name or a gender to a robot) could increase perceptions that the AI is more anthropomorphized.

AI's increased anthropomorphism was shown to reduce the perceptual gap between AI and humans, a factor that can make humans more appreciative of, or averse to, interactions with AI depending upon other contextual factors. For example, previous research on autonomous vehicles found that these vehicles are trusted more when given more anthropomorphic features such as a name, gender, and voice (Waytz et al., 2014). In contrast to anthropomorphization's positive impact on perceptions of AI, anthropomorphization of AI also carries the risk of triggering unfavorable consumer reactions in certain contexts. For example, recent research on humanoid robots in service contexts has identified that consumers often experience discomfort when receiving services from a humanoid robot, an effect that is accentuated when the robot is more anthropomorphized in its appearance (Mende et al., 2019). Research has also found that AI can also be anthropomorphized by giving consumers information about how AI "thinks" (Kim & Duhachek, 2020). This research found that telling people that AI operates via a neural network that approximates human brain function results in greater perceptions of anthropomorphization as compared to telling people that AI cognition was based on a series of rule-based, if/then calculations. These differences in beliefs about the nature and functionality driving AI cognition have been shown to have implications for persuasive attempts by AI agents. For example, Kim and Duhachek (2020) found that a persuasion attempt by an AI was more effective when the message highlighted low (vs. high) construal features, such as explaining "how" (vs. "why") to improve health by using sunscreen or exercising, due to people's naive theory that AI lacks autonomy and thus is incapable of comprehending the motivations driving human actions. However, the differential persuasion effectiveness based on construal level was attenuated when the AI cognitive process was described as mimicking how the human brain works (e.g., a neural network) compared to an AI that relies on a series of rule-based calculations. When AI was described as employing human-like neural network calculations, high construal messages resulted in greater persuasion. Therefore, anthropomorphization is one of AI's design features that can increase or decrease the favorability of response in interactions between AI and consumers. Thus, AI's anthropomorphism is an intentional variation that marketers can strategically manipulate in their AI systems depending upon the needs of the context.

Theory of Mind and Lack of Emotions Among AI. A second set of process variables relate to the theory of mind (Gray et al., 2007). According to the theory of mind perception (Gray et al., 2007), ascribing minds to various agents (e.g., humans, animals, robots) occurs in two dimensions: the capacities associated with "agency" and the capacities associated with "experience". Agency is defined as cognitive "the capacity to plan and act," and experience is defined as relatively emotional and an affective "capacity to sense and feel." (Waytz et al., 2010, p. 383). The two dimensions are continuous, and various entities can be characterized by this two-dimensional model of mind based on the extent of agency and experience capacities that they possess. For example, an adult human is generally perceived by other people to have high capacities associated with agency and experience whereas an infant is perceived to have moderate capacities associated with experience and a lower capacity related to agency due to their premature development of cognitive functions (Gray et al., 2007). According to the theory of mind, AI is an agent with moderate to high agency capacities, such as demonstrating cognitive and computational capacities comparable or superior to humans, depending on domains. However, AI is generally perceived to have far lower experiential and emotional capacities associated with possessing, processing, or expressing emotions. The asymmetry between AI's cognitive and emotional capabilities leads to various downstream consequences. For example, Gray and Wegner (2012) found that the tendency to feel human-like robots as discomforting (i.e., uncanny valley phenomenon) could be explained by the cognitive dissonance generated by the absence of emotions from an agent that is human-like in appearance. In other words, humans tend to view AI as more agentic than experiential and deviations from this norm are perceived more negatively. Huang and Rust (2018) identify four types of intelligence: mechanical (e.g., repetitive tasks), analytical (e.g., basic calculations), intuitive (e.g., synthesizing data to formulate a desired response), and empathetic (e.g., interpreting and generating complex emotional responses based on real time human interactions) intelligence. At present, AI technology has mastered many tasks utilizing the first three forms of intelligence. Tasks using these forms of intelligence tend to score higher in agency as compared to experience. The empathetic realm of intelligence requires both strong agency and experience, and there is disagreement among researchers about the scale and scope of present technologies to meaningfully enact empathetic intelligence in the marketplace.

Consumer research has examined other contexts in which AI's asymmetric cognitive vs. emotional capabilities lead to other downstream consequences for consumers. Garvey et al. (2021) found that consumers were more (less) willing to accept an unexpectedly higher (lower) price for an offering when the offer originated with an AI as opposed to a human agent. This finding was due to differential perceptions of agency. Consumers believed that AI were lower in intentionality such that munificent acts were viewed as less benevolent, as in the case of lower than expected prices, whereas detrimental acts were viewed as less malevolent as in the case of higher than expected prices. Thus, the attributions consumers made about the mind perception of the AI drove their response in both positive and negative directions.

Similarly, experiential perceptions also drive consumer evaluations. Research by Eastwood et al. (2012) in legal and medical decision-making contexts showed that people preferred decisions that were made by humans as compared to AI due to the belief that human decision-makers could better process experiential and intuitive pieces of information as compared to actuarial (AI) systems. Research by Kim et al. (2022) showed that consumers were more willing to behave unethically when interacting with AI as compared to humans because they believed that AI systems did not qualify as moral victims due to their lack of emotional response. As such, deceiving an AI on an insurance claim or a product return did not produce feelings of guilt to the same extent as deceiving a human representative of a firm. These effects stem from differential beliefs about humans and AI abilities to experience negative emotions associated with unethical consumer behaviors. For the same reason, Bigman and Gray (2018) found that individuals are against machines making moral decisions because machines do not have the full range of human capacities associated with thinking and feeling, whereas both of them which are necessary elements to make when making moral decisions. Thus, AI's asymmetric cognitive versus emotional capacities influences AI acceptance when AI are serving both as a moral patient (i.e., a recipient or a victim of a moral decision) and moral agent (i.e., making moral decisions; see Gray, Waytz, & Young, 2012 for a discussion on moral dyads).

In an organizational hiring context, other research showed that people were less accepting of occupational automation of specific jobs when those jobs were viewed as relying on more experiential, as opposed to agentic skillsets (Waytz & Norton 2014). Consistently, AI's replacement of the human workforce in service industries is predicted to occur first in the jobs that are predominantly mechanical and standardized and then shift over to the jobs that require more intuitive and empathetic capabilities (Huang & Rust 2018). These effects are driven by the asymmetry in AI cognitive and emotional capabilities whereby AI excels at the former as compared to the latter. Outside of the human resources domain, Cian and Longoni (2020) found consumers believed AI were low in warmth and thus were less trusting of recommendations for products that were emotional in nature. The sum of this evidence suggests that consumers believe that AI are lower in experiential, emotional and empathy pathways that have significant impacts on subsequent decision-making.

The enhanced unethical behavior toward AI was reduced for consumers who developed social connections with the AI (e.g., perceiving Amazon Alexa as a friend rather than a functional assistant) because social connection increases emotional attachment toward the AI, a factor that neutralizes the tendency to victimize AI (see also Chen, Wan, & Levy (2017) for the link between social disconnection and anthropomorphism tendency).

Beliefs about autonomy and free will. Another key distinction between AI and humans relates to beliefs about intentionality. Research has shown that people hold the lay belief that AI are machines created by humans to serve humans, and as such, they lack autonomous intentionality to achieve their own set of goals and objectives. This lay belief implicates the concept of free will, which was shown to have a systematic influence on human behaviors in the area of effort, self-control, and dishonest behaviors (Vohs and Schooler 2008). Thus, beliefs about free will and intentionality have been studied as important variables in social psychology, and they are also codified in many social norms and rules (e.g., in sports games or legal judgments) (Güroğlu, van den Bos, & Crone, 2009). For example, intentional (vs. non-intentional) violations of law or a sports game's rules tend to receive more severe penalties. The "sting" of intentionality was also documented in social psychology experiments showing, for example, that electric shocks are felt as more painful when inflicted with malicious intentions (vs. not) (Gray & Wegner, 2008). Similarly, consumers believed that human agents making unexpectedly good offers were acting out of charitable intent to a greater degree than AI making the same offer. Thus, the greater perceived intentionality of humans as compared to AI can produce discrepant marketplace effects (Garvey et al., 2021). AI's lack of free will and autonomy also makes its heroic action to be less inspiring. Huang and Chen (2019) found that laudable actions such as rescuing people from a natural disaster was admired to a lesser extent when conducted by a rescue robot (vs. a human rescue expert) due to the absence of benign intentions in AI's actions.

AI Consumer Research Imagined in the Future

AI as a replacement for human interaction. One of the ways that AI poses a major disruption to current human relationships relates to its potential as a means of replacing or enhancing current human interactions. For example, the social media giant Facebook rebranded itself as Meta in fall 2021 to represent the company's shifting focus to building products and experiences in the Metaverse, a virtual hyper-mediated world whereby consumers use virtual reality technology to navigate virtual spaces. The term metaverse originated in a 1992 science fiction novel authored by Neal Stephenson. In the future, consumer experiences may combine technologies such that a poker game may be played in the Metaverse with human players from around the world competing against AI players at a virtual table. In fact, these technologies exist presently. Virtual worlds like Decentraland and Sandbox already allow consumers to buy virtual land, construct virtual business and entertainment experiences and interact with other citizens in these virtual worlds. Entertainment, networking, sports and gaming have been the early focus of these platforms, but the potential is clearly much more.

These rapid developments and their potential to upend the social and work environments raise several new research questions. How is consumer experience different in these worlds? Do all models of decision-making, perception, persuasion, social influence, and other large domains of consumer research immediately carry over to this world? What moderators exist? What role do identity-related factors play? Are identities related to race and gender and other social groups navigated differently in the virtual world? To what extent do consumers view life in a metaverse as satisfying fantasy and escapism goals, and to what extent do they view it as integrating and completing their human existence outside the Metaverse? More fundamentally, to what extent can AI technology satisfy human needs for intimacy, self-expression, emotional support and other fundamental human need states?

These technologies should also transform the nature of work. Virtual meeting software products by Microsoft, Google and other large technology firms have already anticipated how to create virtual meeting spaces using avatars and virtual reality software. With work meetings transpiring in virtual worlds, AI has the potential to further augment these interactions by facilitating the distribution of documents, performing key analyses in response to topics raised in real-time, and providing summaries and transcriptions, as well as drafting reports based on topics. Some research questions that fall out of this interaction are: what role does AI have in focusing and improving collaborative efforts? Does the form of the AI matter? Should it be an embodied AI or a disembodied AI like Apple's Siri? How are group dynamics altered by communication within a metaverse environment?

Consumer privacy. One application of AI relates to data collection and synthesis for future use. Firms collect an ever-increasing amount of data and are often not held accountable for negative externalities to consumers for future data misuse as it can be difficult to prove (Puntoni et al. 2021). Data can be hacked and misused indefinitely. A 2017 report noted 7,859 separate data breaches since 2005 where consumer privacy was compromised by the extraction of personal and sensitive consumer data (Jin, 2018). Identity theft and data misuse present ongoing problems that may be enhanced when AI's capacity to collect volumes of data runs across deviant human hackers seeking to extract data from company systems. Compounding the problem, nearly every consumer has shared data with hundreds of vendors, who often resell data to multiple third-party vendors, thus making it difficult to identify who has access to one's personal data. This environment makes it very difficult to stop hackers from gaining access to consumer data with serious implications for consumer privacy. Regulation lags technology considerably, and consumers often are not aware of the risks and may consent to things they later regret. One consideration for future research is to examine how consumers tradeoff the increased accuracy of more targeted models based on AI calculations with the potential loss of privacy.

AI technology has also been presented as a means of enhancing consumer privacy. Facebook developed an AI technology to combat revenge porn and asked consumers to upload sensitive photos of themselves to allow Facebook's AI to encode these images such that if they ever appeared on their website, the AI technology would delete them. New technology in image recognition has created "adversarial examples" or images that are modified undetectably to the human eye and can fool the most sophisticated AI image recognition software thus casting doubt over whether Facebook can really protect consumer privacy in the event they are victimized, for example, by a revenge porn attack. Facebook received negative backlash for its attempt to ensure consumer privacy and many consumers expressed an unwillingness to trust Facebook or its AI with their sensitive erotic photos. Thus, it seems that the relationship between corporate AI and consumer privacy perceptions is still developing and is likely to change considerably.

Religion and technology. One societal trend with potential implications for the emergence of AI relates to the secularization of American society. Gallup has polled on religious identification since the 1930's and noted for the first time in 2021 that the percentage of Americans claiming an affiliation with a house of worship fell below a majority for the first time in their polling history (47%). In contrast, 70% of Americans were affiliated with a house of worship in 1999. The rapid secularization of society, particularly among younger Americans, is likely to bring forth widespread changes to American views on religious morality. Given that younger Americans are also more likely to engage with AI technology, one possibility is that consumers view emerging technologies as a replacement for traditional morality. One individual consumer difference variable that could be examined relates to the tendency to view technology in spiritual terms. Just as consumers anthropomorphize technology, consumers may similarly trend toward viewing AI with superhuman intelligence in specific domains as occupying a role similar to the traditional role fulfilled by religion and notions of God. Research by Li, Kim and Duhachek (2022) has begun to examine the intersection of religion and AI on key outcomes. One possibility is that superhuman AI makes people more likely to turn toward a more humanist philosophy that elevates concern for humans over technology. Or it is possible that this trend goes the other way, and people are less humanistic in response to superhuman AI intelligence. Research is needed to examine whether the trend toward secularization leads to the replacement of religious moral systems with technologically based ones.

Partially humanized machines and dehumanized humans. In 1950, British mathematician Alan Turing proposed an innovative idea that human intelligence associated with the effective use of available information and reasoning ability could be replicated by the machines if appropriate conditions are provided (Turing & Haugeland, 1950), which is considered by many as one of the most influential conceptualization of what has now become the artificial intelligence that is around us. Since the inception of the AI concept and several breakthrough moments in AI history (e.g., Dartmouth summer workshop on AI in 1956 or IBM's Deep Blue defeating human Chess champion in 1997), the progress in AI technology has been fueled by the desire to mimic human intelligence. The ambition to create an AI comparable to humans is also exhibited by the effort exerted to make human-like AI not only in their thinking styles but also in their appearance (e.g., face, body type, possession of voice, gender, and other identities). The emergence of human-like AI is a natural consequence of the human tendency to anthropomorphize various entities, including robots, algorithms, autonomous vehicles, chatbots, and virtual agents. As human-like AI has become more pervasive, concerns have been raised regarding the future of human identity and the sustainable coexistence of humans and machines. As portrayed in many sci-fi dramas (e.g., "Westworld" or "Humans") and movies (e.g., "The Terminator" or "I, Robot"), dehumanization has been raised as one of those concerns. In some extreme fictional scenarios, the dehumanization process is often depicted as a result of humans losing hegemony to machines as artificial intelligence overcomes human intelligence in many domains. Research into this issue has examined the context of robots replacing humans in workplaces, a process called botsourcing. Jackson et al. (2020) found that the salience of robot workforce shed light on the commonality among humans and reduced the biases in their intergroup relations (i.e., "panhumanism"). For example, they found that the prevalence of the robot workforce in human workplaces made the people less prejudiced toward outgroup individuals (e.g., a person with a different race or religion) in various decisions related to resource allocations.

Dehumanization could also occur during the human acculturation to machines that represent humanness only in a narrow sense (e.g., a humanoid sex robot designed only for sexual pleasure or a humanoid soldier designed with the sole intent of killing enemy human soldiers). Exposures to such partially humanized machines and the blurred boundary between humans and robots due to their similarity may distort the way humans are perceived in the future. For example, children frequently exposed to partially humanized machines may have limited opportunities to learn about humanity in its entirety. To be more specific, researchers have found that focusing on specific physical attributes of a person (e.g., sexual attractiveness, physical strength) could make the person's mental capacities (e.g., cognitive abilities) less salient, leading to greater objectification of the person (Gray et al., 2011, see also Weihrauch & Huang, 2021). Thus, repeated exposure and acculturation to human-like AI agents that are designed to perform only specific tasks (e.g., fighting), and, are endowed with only some human traits, could distort the traditional interhuman relations built on a holistic perspective and lead to a greater tendency to dehumanize and objectify other individuals (Orehek et al., 2018; see also Haslam 2006 for a review of the literature on dehumanization).

Another implication of the dehumanization process surrounding AI relates to how violence or verbal abuse toward AI is viewed. A new app-based AI called Replika allows users to have emotional conversations with an avatar-based AI technology. One phenomenon observed by developers is a tendency for some consumers to engage in higher levels of verbal abuse with these technologies. Perhaps this trend is due to the fact that consumers are less likely to perceive AI as a moral victim. Similarly, Apple has reported an alarmingly high percentage of messages directed toward its AI Siri have been abusive or violent. Whether this trend reveals a dark compulsion to further abuse others or whether these actions make abuse of other people less likely is not well understood. At the very least, these trends suggest that consumers dehumanize and detach moral compassion for AI in many interactions.

Thus, future research should examine the impact that various types of AI agents and robots may have on our tendencies toward violence or compassion. Research is needed to determine whether these abusive interactions with AI precipitate greater violence or have negative spillovers that harm society. It is possible that such interactions give consumers a different perspective on humanness and change existing balances and perceptions of morality. If society views the abuse of robots as immoral, what safeguards can be implemented to ensure the proper treatment of robots and AI? One possibility is that these behaviors necessitate the construction of a robot Bill of Rights that guides and regulates human behavior toward AI.

Conclusion

Consumer experience has been driven by technology since ancient times. The pace of technological change in AI is sure to dramatically change the future of consumption. The current chapter is designed to point out pathways for consumer researchers to pursue in the direction of providing a better understanding of how consumers interact with AI now and into the future.

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