Article

Journal of Marketing
2021, Vol. 85(1) 131-151

DOI: 10.1177/0022242920953847
journals.sagepub.com/home/jmx
SAGE

Consumers and Artificial Intelligence: An Experiential Perspective

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Editor's Note: This article is part of the JM-MSI Special Issue on "From Marketing Priorities to Research Agendas," edited by John A. Deighton, Carl F. Mela, and Christine Moorman. Written by teams led by members of the inaugural class of MSI Scholars, these articles review the literature on an important marketing topic reflected in the MSI Priorities and offer an expansive research agenda for the marketing discipline. A list of articles appearing in the Special Issue can be found at http://www.ama.org/JM-MSI-2020.

MARKETING SCIENCE INSTITUTE

Abstract

Artificial intelligence (AI) helps companies offer important benefits to consumers, such as health monitoring with wearable devices, advice with recommender systems, peace of mind with smart household products, and convenience with voice-activated virtual assistants. However, although AI can be seen as a neutral tool to be evaluated on efficiency and accuracy, this approach does not consider the social and individual challenges that can occur when AI is deployed. This research aims to bridge these two perspectives: on one side, the authors acknowledge the value that embedding AI technology into products and services can provide to consumers. On the other side, the authors build on and integrate sociological and psychological scholarship to examine some of the costs consumers experience in their interactions with AI. In doing so, the authors identify four types of consumer experiences with AI: (1) data capture, (2) classification, (3) delegation, and (4) social. This approach allows the authors to discuss policy and managerial avenues to address the ways in which consumers may fail to experience value in organizations' investments into AI and to lay out an agenda for future research.

Keywords

artificial intelligence, AI, customer experience, technology marketing, privacy, discrimination, replacement, alienation

Not long ago, artificial intelligence (AI) was the stuff of science fiction. Now it is changing how consumers eat, sleep, work, play, and even date. Consider the diversity of interactions consumers might have with AI throughout the day, from Fitbit's fitness tracker and Alibaba's Tmall Genie smart speaker to Google Photo's editing suggestions and Spotify's music playlists. Given the growing ubiquity of AI in consumers' lives, marketers operate in organizations with a culture increasingly shaped by computer science. Software developers' objective of creating technical excellence, however, may not naturally align with marketers' objective of creating valued consumer experiences. For example, computer scientists often characterize algorithms as neutral tools evaluated on efficiency and accuracy (Green and Viljoen 2020), an approach that may overlook the social and individual complexities of the contexts in which AI is increasingly deployed. Thus, whereas AI can improve consumers' lives in very concrete and relevant ways, a failure to incorporate behavioral insight into technological developments may undermine consumers' experiences with AI.

This article aims to bridge these two perspectives: on one side, we acknowledge the benefits that AI can provide to consumers. On the other side, we build on and integrate sociological and psychological scholarship to examine the costs consumers can experience in their interactions with AI. Exposing the tension between these benefits and costs, we offer

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recommendations to guide managers and scholars investigating these challenges. In so doing, we respond to the call from the Marketing Science Institute to examine "the role of the human/tech interface in marketing strategy" and to offer more scholarly attention to situations where "customers face an array of new devices with which to interact with firms, fundamentally altering the purchase experience" (Marketing Science Institute 2018).

We begin by offering a framework that conceptualizes AI as an ecosystem with four capabilities. We focus on the consumer experience of these capabilities, including the tensions felt. We then offer more insights into the experience of these tensions at a macro level by exposing relevant and often explosive narratives in the sociological context and at the micro level by illustrating them with real-life examples grounded in relevant psychological literature. Using these insights, we provide marketers with recommendations regarding how to learn about and manage the tensions. Paralleling the joint emphasis on social and individual responses, we make recommendations outlining both the organizational learning in which firms should engage to lead the deployment of consumer AI and the concrete steps they should take to design improved consumer AI experiences. We close with a research agenda that cuts across the four consumer experiences and suggests ideas for how researchers might contribute new knowledge on this important topic.

Understanding the Consumer AI Experience

We conceptualize AI as an ecosystem comprising three fundamental elements—data collection and storage, statistical and computational techniques, and output systems—that enable products and services to perform tasks typically understood as requiring intelligence and autonomous decision making on behalf of humans (Agrawal, Gans, and Goldfarb 2018). These elements are associated with capabilities (i.e., listening, predicting, producing, and communicating). Data collection devices listen in the broad sense of gathering information from different sources; for example, product sensors scan the environment, and wearable devices record physical activity. Algorithms leverage this information to predict; for example, Spotify serves music suggestions through personalized playlists. Finally, output systems produce a response or communicate with consumers, for example by directing a vehicle or responding through consumer interfaces like Baidu's Duer.

To articulate a customer-centric view of AI, we move attention away from the technology toward how the AI capabilities are experienced by consumers. "Consumer experience" relates to the interactions between the consumer and the company during the customer journey and encompasses multiple dimensions: emotional, cognitive, behavioral, sensorial, and social (Brakus, Schmitt, and Zarantonello 2009; Lemon and Verhoef 2016). Our framework is built on four experiences that reflect how consumers interact with the four AI capabilities (Figure 1). This experiential perspective helps shed light on the affective and symbolic aspects of technology consumption in addition to the utilitarian and functional ones (Mick and Fournier 1998). "Data capture" is the experience of endowing individual data to AI, "classification" is the experience of receiving AI's personalized predictions, "delegation" is the experience of engaging in production processes where the AI performs some tasks on behalf of the consumer, and "social" is the experience of interactive communication with an AI partner.

For each experience, we identify benefits and costs from a consumer perspective and propose that managers qualify their focus on the former by paying attention to the latter: a data capture experience may serve or exploit consumers, a classification experience may understand or misunderstand them, a delegation experience may empower or replace consumers, and a social experience may connect or alienate them. We next examine each of these experiences, their social science connections, managerial implications, and future research directions.

The AI Data Capture Experience

The listening capability enables AI systems to collect data about consumers and the environment in which they live. We conceptualize the resulting experience as "data capture," which includes the different ways in which data are transferred to the AI. Data can be intentionally provided by consumers, albeit with different degrees of understanding of the process: consumers share data when there is little or no uncertainty about how the data will be used and by whom, or consumers surrender data when this uncertainty is high (Walker 2016). Data can also be obtained by AI from the "shadows" consumers leave behind when they engage in daily activities, as in the case of a shopper perusing a store equipped with facial recognition technology or of an iRobot Roomba creating a map of a residential space (Kuniavsky 2010).

The data capture experience provides benefits to consumers because it can make them feel as if they are served by the AI: the provision of personal data allows consumers access to customized services, information, and entertainment, often for free. For example, consumers who install the Google Photos app let Google capture their memories but in return get an AI-powered assistant that suggests context-sensitive actions when viewing photos. Access to customized services also implies that consumers can enjoy the outcome of decisions made by digital assistants, which effectively match personal preferences with available options without having to endure the cognitive and affective fatigue that decision making can entail (André et al. 2018). Finally, access to customized services offers unprecedented opportunities for self-improvement. Consider one of the projects within Alphabet, in which data from smartphones, genomes, wearables, and ambient sensors are combined to drive personalized health care (Kuchler 2020).

Despite AI's ability to predict and satisfy preferences, consumers can feel exploited in data capture experiences, mainly

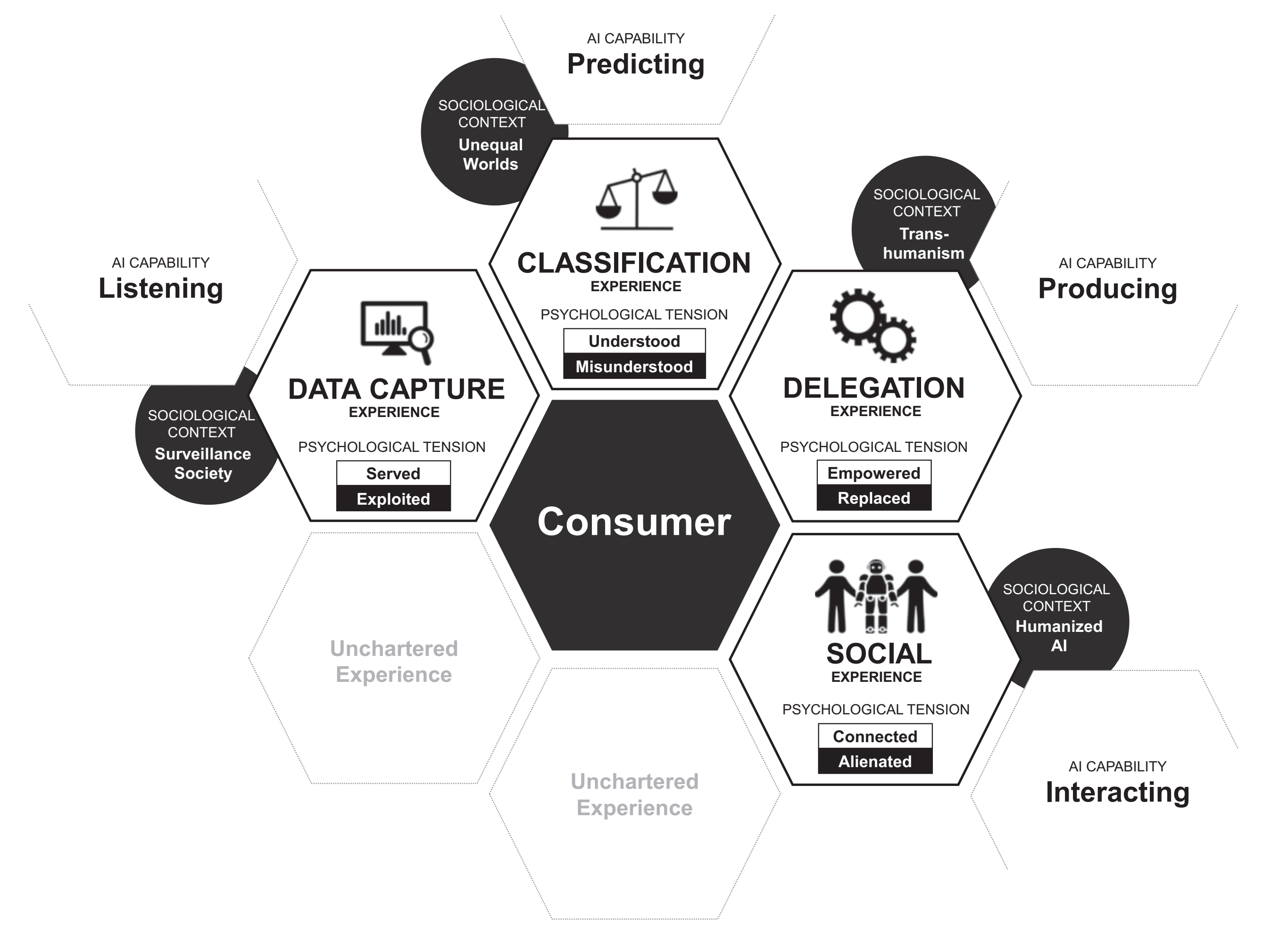

Figure 1. The consumer AI experience.

because they do not understand AI's operating criteria. This can be attributed to several features of AI. First, the modalities of data acquisition are becoming increasingly intrusive and difficult to avoid. Second, even when consumers intentionally share information, they are not aware of how this information is aggregated over time and across contexts. Finally, data brokers are largely unregulated and often lack transparency and accountability (Grafanaki 2017). As a result, data capture experiences may threaten consumers' ownership of personal data and challenge personal control, that is, the feeling that events are determined by the self rather than by others or by external forces and can be stirred toward desired outcomes (DeCharms 1968). We examine the consequences of this loss of control next from both a sociological and psychological perspective.

Sociological Context: The Surveillance Society Narrative

In popular culture, lack of ownership over personal data has been frequently associated with a loss of personal control stemming from technology's threatening potential to enable monitoring of human behavior. Stories such as George Orwell's *1984* or Philip K. Dick's *Minority Report* envision systems of oppression in which, due to lack of privacy and constant surveillance, people can no longer control their destiny. This dystopian imagination is echoed in sociological scholarship that associates data capture with the rise of a capitalist marketplace in which private information becomes the central form of capital (Zuboff 2019).

Such dystopian concerns strike a resonant chord when considering Google's move in the early 2000s to transform consumer data from a by-product into an economic asset that formed the basis of a new type of commerce driven by the ability to colonize the consumer's private experience. This commerce contributes to a surveillance marketplace, in which data surplus is "fed into advanced manufacturing processes known as 'machine intelligence' and fabricated into *prediction products* that anticipate what you will do now, soon, and later" (Zuboff 2019, p. 14, italics in the original). To illustrate the power of this commerce, targeted ads based on personality characteristics inferred from the analysis of Facebook likes in combination with online survey questions can increase conversion rates by about 50% (Matz et al. 2017). In 2018, Facebook's revenues from the sales of such tailored ads was close to $56 billion (Moore and Murphy 2019).

From the perspective of this narrative, not only are technology companies continually required to find new ways to make monitoring and surveillance palatable to consumers by linking it to convenience, productivity, safety, or health and well-being (Bettany and Kerrane 2016), but they must also constantly push the boundaries of what private information consumers should share (Giesler and Humphreys 2007) through a complex landscape of notifications, reminders, and nudges intended to initiate behavioral change. Thus, as consumer behavior becomes increasingly retailored to the exigencies of behavioral futures, AI can transform consumers into subjects who are complicit in the commercial exploitation of their own private experience, thereby undermining personal control and promoting the concentration of knowledge and power in the hands of those who own their information.

Psychological Perspective: The Exploited Consumer

Data capture experiences are characterized by an underlying tension: consumers recognize that data capture allows AI to serve them through customization, but AI's inherent lack of transparency makes them feel exploited. These feelings of exploitation are fueled by actual and perceived loss of personal control, with important psychological consequences (Botti and Iyengar 2006). The first of such consequences is negative affect, which can turn into demotivation and helplessness. Consider the case of Leila, a sex worker who shielded her identity on her Facebook account and reported being shocked to see some of her regular clients recommended by the "People You May Know" function. According to Leila, "the worst nightmare of sex workers is to have your real name out there, and Facebook connecting people like this is the harbinger of that nightmare." For Leila, like for domestic violence victims or political activists, privacy invasion is not only frightening, it may become a matter of life, death, or time in jail (Hill 2017).

As being in control is a basic need and a precondition of psychological welfare (Leotti, Iyengar, and Ochsner 2010), the second consequence of loss of personal control may be moral outrage. Consider the case of a German consumer who requested his own data from Amazon and received transcripts of Alexa's interpretations of voice commands, even though he did not own any Alexa devices. The consumer relayed his story to a local magazine, which attempted to identify the consumer whose privacy had been compromised. The magazine staff involved in this experience described it as follows: "[we were able to] navigate around a complete stranger's private life without his knowledge, and the immoral, almost voyeuristic nature of what we were doing got our hair standing on end" (Brown 2018).

The third consequence of loss of personal control relevant to data capture experiences is psychological reactance, a state in which a person is motivated to restore control after a restriction (Brehm 1966), which causes more negative evaluations of and hostile behaviors toward the source of the restriction. In marketing, reactance can decrease the likelihood to repurchase and follow recommendations (Fitzsimons and Lehmann 2004). Illustrating reactance in AI data capture experience is Danielle, a U.S. consumer who installed Echo devices throughout her home, believing Amazon's claims that they would not invade her privacy. When one of her Alexas recorded a private conversation and sent it to a random number in her address book, Danielle said "I felt invaded" and concluded, "I'm never plugging that device in again, because I can't trust it" (Horcher 2018).

In summary, consumers may experience data capture as a form of exploitation: whereas technology companies, firms, and governmental agencies gain financial and political power, consumers lose ownership of their data and feel a loss of control over their lives. As we discuss next, managers should gain a better understanding of feelings of exploitation, as they prevent consumers from seeing the value firms can provide through data capture. This understanding starts at the organizational level and is then translated into decisions about experience design.

Managerial Recommendations: Understanding the Exploited Consumer

Organizational learning. A central programmatic task in addressing the issue of consumer exploitation in AI data capture experiences involves determining and enhancing the organization's level of awareness regarding the sociological and psychological costs raised in the previous sections. Companies should strive toward greater organizational sensitivity around consumer privacy and the current asymmetry in the level of control over personal data. For instance, they should use netnographic observation or sentiment analysis to listen empathetically and at scale to consumers who have experienced exploitation in AI data capture experiences. Furthermore, rather than accepting the surveillance society narrative at face value, firms can use these tools to understand when, how, and whether their own data capture experiences play into versus subvert this narrative. Likewise, companies should draw on insights by privacy scholars and activist movements to question their taken-for-granted beliefs. In doing so, for instance, companies could realize that their own view on privacy default settings might differ markedly from that of a vulnerable consumer group and adjust their processes accordingly (Martin and Murphy 2017).

Organizational learning can also extend beyond the boundaries of the individual firm to encompass other institutions. First, companies could sponsor research aimed at understanding the influence of surveillance society–style thinking on their culture and practice, as well as its negative impact on marketing activities and consumers. Second, companies could adopt a more communal approach to sharing individual organizational learning with other firms, industry associations, educators, and the media. Third, industry groups could collaborate with scholars to create and adopt an algorithm bill of rights for individuals (Hosanagar 2019), which some AI experts have proposed should include a right to transparency, for example, "the right to know when an algorithm is making a decision about us, which factors are being considered by the algorithm, and how those factors are being weighted" (Samuel 2019a).

Experience design. Using this organizational learning, organizations should design improved AI data capture experiences. Recent regulations, such as the European Union's General Data Protection Regulation, aim to limit exploitation by making organizations responsible for giving consumers the possibility to opt into specific data collection processes (e.g., cookies) and to ask for greater clarity on how these data are used.

However, as AI becomes more pervasive and ubiquitous, ensuring consumer consent at all steps of the customer journey may result in an overload of choice and information that decreases instead of increases personal control (Iyengar and Lepper 2000) and exacerbates the negative affective and behavioral reactions illustrated previously. Interventions related to the way in which options are presented—the choice architecture—can reduce the cognitive and affective costs associated with excessive information and choice (Chernev, Böckenholt, and Goodman 2015) and thereby give consumers greater control over their data without overloading them.

Among such interventions, including default options has proven especially effective in facilitating decision making as well as influencing specific behaviors (Thaler and Benartzi 2004). Because individuals tend to passively accept defaults instead of exercising their right to opt out, the selection of defaults by choice architects may lead to suboptimal outcomes when it does not properly consider preference heterogeneity. The personalization of defaults could mitigate this issue (Sunstein 2015), and AI itself could assist consumers in the automatic implementation of preferences about how their data are captured and analyzed.

More broadly, organizations can limit consumer exploitation by playing an active role in educating consumers about the costs and benefits entailed in AI data capture experiences. For example, the recently overhauled Google Home app clearly communicates what user data have been stored and why. Understanding the potential for exploitation in data capture experiences is useful not only for managers interested in maximizing the value provided to consumers served by the AI but also for researchers interested in uncovering the sociological and psychological underpinnings of the tension that accompanies this experience.

Future Research on the AI Data Capture Experience

Sociological research questions. Future research should investigate how sociocultural forces affect feelings of exploitation in data capture experiences. People from poorer childhood backgrounds have a lower sense of control than those from wealthier ones (Mittal and Griskevicius 2014), and collective self-construal is associated with a lower desire for choice freedom and control (Bernthal, Crockett, and Rose 2005; Markus and Schwartz 2010). Thus, both consumers' socioeconomic status (Research Question 1A, or RQA1; see Table 1) and prevailing cultural norms (RQA2) could influence consumers' propensity to feel and be exploited by AI. Other factors, such as education, political orientation, gender, and race (RQA3) could be examined using an intersectionality lens (Crenshaw 1989).

Future research should also explore how the cultural cognitive, normative, or regulatory legitimacy of AI changes over time to influence consumer reactions to data capture (Acquisti, John, and Loewenstein 2012; Humphreys 2010), particularly in light of AI's rapid diffusion in the marketplace. For example, researchers could study how and when increasing levels of familiarity with AI may reduce consumer sensitivity toward exploitation (RQA4).

Psychological research questions. An interesting avenue for future research consists of exploring the role that psychological processes play in interpreting AI data capture experiences as exploitative. For example, researchers could study the role of motivated reasoning (Kunda 1990) in shaping consumer affective reactions to data capture experiences (RQA5): strongly held goals may motivate consumers to accept greater risk of exploitation when the AI is seen as a conduit to goal completion, mitigating negative emotional responses.

Other important open questions concern how the source and type of data used by the AI affect its potential to exploit. For example, an AI-enabled device that is constantly listening to biometric data could, over time, become paradoxically less invasive than one that listens only when activated (Turkle 2008). Complementing recent scholarship on the consequences of personal quantification (Etkin 2016), future research should address how the frequency of data capture (e.g., intermittent vs. continuous) affects perceived exploitation (RQA6). As another example, information collected about the physical environment, such as that acquired by a smart refrigerator, may be less likely to generate feelings of exploitation than information collected about the self, such as that acquired by a fitness tracker (RQA7).

Feelings of exploitation may also differ on the basis of the physical context of consumption (RQA8). Current attempts by companies like Amazon or Google to redefine the family home as a space accessible to corporations rather than a private space may attenuate or exacerbate these feelings. Similarly, physical features of the environment where data collection takes place may differently trigger concerns about exploitation. For example, crowded environments lead to a loss of perceived control, which could decrease willingness to provide data. Concerns about exploitation may also differ on the basis of the device used to interact with AI (RQA9), as research has shown that consumers are more likely to self-disclose when using smartphones versus PCs (Melumad and Meyer 2020).

Table 1. Consumers and AI Experience: Emerging Research Questions (RQs).

A: The AI Data Capture Experience
RQA1: How does socioeconomic status influence the likelihood of feeling exploited?
RQA2: How do cultural norms influence the likelihood of feeling exploited?
RQA3: How does intersectionality normalize or problematize exploitation?
RQA4: How does the diffusion of AI affect feelings of exploitation over time?
RQA5: How does motivated reasoning shape consumer affective reactions in data capture experiences?
RQA6: How does the frequency of data capture affect perceived exploitation over time?
RQA7: How are feelings of exploitation influenced by the nature of the data collected (e.g., environmental, behavioral, physiological)?
RQA8: How does the physical context of data collection affect the likelihood of feeling exploited?
RQA9: Does the experience of data capture depend on the device the consumer is using?
RQA10: When and how will consumers sabotage data collection by AI in response to feelings of exploitation?
B: The AI Classification Experience
RQB1: How do individual differences in awareness of discrimination affect whether a consumer feels misunderstood by AI?
RQB2: How do the social classifications inscribed into AI solutions shape consumer behavior and choices?
RQB3: How do consumers infer which variables AI is using to make personalized predictions?
RQB4: Which types of inferred classifications are more likely to make consumers feel misunderstood?
RQB5: How do uniqueness versus belonging motives affect the likelihood of feeling misunderstood?
RQB6: How does the nature of the task influence the likelihood of feeling misunderstood?
C: The AI Delegation Experience
RQC1: How do feelings of being replaced depend on the perceived "humanness" of an activity?
RQC2: How does feeling replaced by AI affect the perceived acceptability of various behaviors intended to protect or promote the self?
RQC3: As the range of tasks that AI can perform increases over time, how do normative task boundaries around humans versus algorithms shift?
RQC4: What specific consumption contexts make delegation to AI more psychologically aversive?
RQC5: Do consumers compensate for feelings of being replaced by AI in nonconsumption domains?
RQC6: How do instrumental versus symbolic consumption motives determine perceptions of being replaced?
RQC7: Is the likelihood of feeling replaced affected by whether consumers focus on consumption outcomes versus processes?
RQC8: When and how do consumers respond to threats of replacement by AI by constraining the AI's production capability?
D: The AI Social Experience
RQD1: How do antibias beliefs affect alienation in social experiences?
RQD2: How do cultural differences influence consumer perceptions of social experiences?
RQD3: What are the consequences of AI-enabled social experiences for important societal processes such as children's socialization and gender relations?
RQD4: When are customers more likely to objectify AI in response to alienation?
RQD5: How does the timing of disclosure influence the likelihood of consumer alienation?
RQD6: What is the influence of situational characteristics on alienation?
RQD7: What is the role of brand equity in reducing or facilitating alienation?
E: Interrelationship Between AI Experiences
RQE1: How do the ways in which consumers experience data capture influence perceived resource accessibility in a classification experience?
RQE2: Does aggressive data capture strengthen or weaken social inclusion?
RQE3: Does involving consumers in the validation of assumptions about their preferences shift a classification experience to feel more like a delegation experience?
RQE4: Do changes in feelings of control lead to parallel shifts in data capture and delegation experiences?
RQE5: Do changes in consumer self-identity concerns lead to parallel shifts in classification and social experiences?
RQE6: Are data capture experiences less aversive when demands for data increase together with feelings of empowerment from delegation experiences?
F: Unchartered AI Experiences
RQF1: How does the learner–AI interaction shape learning experiences and affect student satisfaction, motivation, and learning?
RQF2: How does the valence of learning experiences depend on identity relevance and internal attribution of learning outcomes?
RQF3: What motivates consumers to have AI-enabled companionship experiences?
RQF4: What factors determine whether consumers perceive companionship experiences as deceptive or alienating?
RQF5: How do AI solutions that permeate epistemic boundaries between human and machine impact consumer autonomy?
RQF6: How does AI perceive and experience the world and marketplace, and how can firms design these experiences effectively?

Finally, when consumers cannot or do not want to take advantage of the benefits of data capture, psychological reactance toward AI may manifest in adversarial user behaviors, as suggested by the experience of Danielle. Future research can explore the factors that lead consumers to respond to feelings of exploitation with behaviors like sabotaging AI by disabling sensors' inputs, intentionally providing false data by creating fake user profiles, or adopting antisurveillance outerwear to confuse the algorithms controlling facial recognition systems (RQA9).

The AI Classification Experience

Firms leverage the predicting capability of AI to create ultra-customized offerings and maximize engagement, relevance, and satisfaction (Kumar et al. 2019). Sophisticated algorithms consider a wide variety of information, including the characteristics of both current and past consumers. For example, Netflix uses AI to offer personalized movie recommendations based on not only individuals' past viewing history and that of other viewers but also contextual information such as day of the week, time of day, device, and location (Kathayat 2019). Netflix even uses AI to select videoframe thumbnails that can increase subscribers' likelihood to click on a specific show (Yu 2019). Even though prediction interfaces use individual and contextual information, they often refer to information related to other users either explicitly by mentioning others when framing recommendations (e.g., Amazon noting "customers who bought this also bought") or implicitly by organizing recommendations in terms of communities of users or taste niches (e.g., Amazon Prime drawing attention to movies for "period drama fans"). As consumers are often unaware of the workings of algorithms, they may infer that these recommendations are based on being classified as a certain type of person. Such inferences are amplified by the human tendency for categorical thinking in person- and self-perception (Turner and Reynolds 2011). For example, consumers engage in categorical inference making when they are served behaviorally targeted ads: they attribute the ads they receive to the advertiser labeling them as a person with specific tastes (Summers, Smith, and Reczek 2016). We conceptualize the "classification experience" as one in which consumers perceive AI-enabled personalized predictions to be the result of being classified as a certain consumer type.

Classification experiences can be positive because they lead consumers to feel deeply understood either objectively or subjectively. For example, consumer categorizations can be valuable to affirm the self: personalized offers that indicate membership in an aspirational group may help consumers satisfy identity motives when they are perceived as social labels (Summers, Smith, and Reczek 2016). Framings based on other users, such as "people who like this also like," make recommendations more persuasive than those based on the product, such as "similar to this item" (Gai and Klesse 2019), further suggesting that the experience of feeling classified by AI as a certain type of person is often positive. These findings resonate with research demonstrating the psychological benefits of group membership (Reed et al. 2012; Turner and Reynolds 2011). However, classification experiences may also lead consumers to feel misunderstood when they perceive AI as having inaccurately assigned them to a group or as having made biased predictions on the basis of group assignment. At the societal level, classification by AI is linked to a dystopic narrative in which access to resources and freedom is restricted for some groups.

Sociological Context: The Unequal Worlds Narrative

Classification experiences do not exist in a sociological vacuum but are shaped by popular myths. Science fiction stories such as Neill Blomkamp's *Elysium* have routinely imagined deeply divided police states in which the ruling class draws on algorithms to sustain a regime of inequality and fear. Sociological scholarship on the politics of algorithms (Seaver 2019) has also drawn on this popular imagination to theorize AI in the context of rationalization and quantification (Porter 1996), automated inequality (Dormehl 2014a), uneven information landscapes (Eubanks 2018), and the historical rise of "algorithms of oppression" (Noble 2018) or "weapons of math destruction" (O'Neil 2016). Emphasizing the intersectionality of race and gender with antisemitism, poverty, unemployment, and social class (Crenshaw 1989), these investigations of AI's potential for social classification are particularly insightful. AI is feared to privilege whiteness and undermine the identity projects of minorities (Dormehl 2014b). This contention is consistent with research on the market (bio)politics of race, which has consistently shown the inherently discriminatory potential of marketized representations of culture and ethnicity, and it is also supported by economic critiques that warn against the monopolization of information by a centralized system (Hayek 1945; Polanyi 1948).

Consider Google's corporate mission to "organize the world's information." From an unequal worlds perspective, such a statement is far from politically neutral; rather, it exemplifies the operation of seemingly benign appeals to data automation and quantification in a market that sanctions the production of biased information. In such an ideological system, the designers of an AI-enabled college admissions software, for instance, may be convinced that AI can help combat human selection bias. However, because "algorithms that rank and prioritize for profits compromise our ability to engage with complicated ideas" (Noble 2018, p. 118), the resulting AI experience may not only reduce the complex experiences of targeted marginalized populations to a set of more simplified sociodemographic attributes or stereotypes but it may also unintentionally expose marginalized applicants to racial profiling, misrepresentation, and economic redlining when used by admissions officers. Likewise, problems can arise when banks use AI to decide whether a consumer is worthy of borrowing money. Although algorithms may make the selection process more efficient, they can also systematically exclude consumers who live in a neighborhood with higher credit defaults (Brown

2019). The realization that AI can result in racial and social groups experiencing discrimination is an important backdrop for a psychological analysis of consumers' feelings of being misunderstood.

Psychological Perspective: The Misunderstood Consumer

Classification experiences are characterized by an underlying tension between feeling understood and misunderstood. Consumers can feel misunderstood because of perceived incorrect classification, discriminatory use of classification, or a combination of the two. First, consumers are likely to feel misunderstood when they perceive the identity implied by the AI's output as incorrect, either because it is factually inaccurate or because it is based only on one identity, whereas most individuals identify with a host of personal and social selves (Oyserman 2009). Identity-based consumer behavior is often the result of a negotiation between belonging and uniqueness motives playing out across this constellation of identities (Chan, Berger, and Van Boven 2012). In situations where consumers perceive AI predictions to be driven by their membership in a group, uniqueness motives may become relatively more salient. When this happens, group identity appeals may backfire if they are believed to threaten individual agency (Bhattacharjee, Berger, and Menon 2014). This negative response is especially likely when the consumer perceives the identity assigned to them by the AI as noncentral or dated, as in this excerpt from a Spotify Community post (Grandterr 2019):

> "The recommendations s*ck:
>
> - Listened to a few anime covers, now all my "Discover Weekly" is filled with disgusting covers. I'm trying to "not like" all of them, but it doesn't work .... I've stopped listening to rock years ago and still get rock recommendations."

From this consumer's perspective, the AI used by Spotify seems to have decided that they like anime covers and rock, putting them in a category that they reject or do not see as capturing their multifaceted and evolving self. The consumer is frustrated not only with being misunderstood by the AI, but also with their perceived inability to alter such misunderstanding.

Second, consumers may also feel misunderstood when they fear AI is using a social category in a discriminatory way to make biased predictions about them. This is particularly problematic in contexts where these predictions may enhance consumers' vulnerability because they restrict access to marketplace resources (Hill and Sharma 2020). For example, fintech companies increasingly use easily accessible digital information such as individuals registering on a webpage to predict their payment behavior and defaults and therefore judge their creditworthiness (Berg et al. 2020). Consider this tweet by a software developer, David Heinemeier Hansson (@dhh, November 7, 2019, https://twitter.com/dhh/status/1192540900393705474):

> "The @AppleCard is such a f*ing sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple's black box algorithm thinks I deserve 20x the credit limit she does..."

This consumer is frustrated because of the AI's inability to understand the reality of his household's finances, but he is also morally outraged because he thinks that his wife's denial of credit was based on her gender. Perception of vulnerability such as this can have negative effects on the self-concept. This can occur, for example, when minorities whose financial choices are systemically restricted then frame the self as "fettered, alone, discriminated, and subservient" and experience reductions in self-esteem and self-efficacy (Bone, Christensen, and Williams 2014).

Consumers can also experience a combination of the two ways of feeling misunderstood mentioned previously: they can be incorrectly assigned to a category and this incorrect assignment can exacerbate existing limitations on choice and freedom for vulnerable consumers. Facial recognition software, for instance, uses AI to identify a person by comparing a target facial signature to databases of known images. The range of applications of such software includes mobile devices (e.g., Apple's Face ID), social media (e.g., Facebook's tagging feature), and physical spaces (e.g., airport customs officials). Whereas a failure of Apple's Face ID to start one's own device may result in frustration, incorrect identification in other applications may result in ethical violations. Consider the open letter to Amazon CEO Jeff Bezos written by the Congressional Black Caucus on the potential danger caused by Amazon's facial recognition tool, Rekognition:

> Communities of color are more heavily and aggressively policed than white communities....We are seriously concerned that wrong decisions will be made due to the skewed data set produced by what we view as unfair and, at times, unconstitutional policing practices. (Richmond 2018)

In a subsequent test, Rekognition indeed incorrectly matched 28 current members of the U.S. Congress with people who had committed a crime, and the false matches were disproportionately for people of color (Snow 2018). In June 2020, Amazon suspended police use of this technology (Fitch 2020). We next examine how managers can understand and address the risk of consumers feeling misunderstood.

Managerial Recommendations: Understanding the Misunderstood Consumer

Organizational learning. How does an organization best surface and address accounts of biased treatment? Unlike data capture errors, which may be lagged and hard to correct in real-time, classification errors produce signals soon after they occur. They also happen in very different parts of an organization. For instance, if an AI system has rejected a college applicant due to a biased algorithm, it is likely to assume that such a classification error will almost immediately surface in the college's admissions department and data—data that in turn might be used to structure the next round of applications.

Owing to this data dependency, organizations may not even be aware that a given distribution or algorithm is the result of a classification error. In the case of a college, for instance, classification might be regarded as a natural outcome of the competitive process by those in charge of managing the admissions process. Thus, unlike data capture failings that require the specific attention of software programmers and data scientists, addressing classification errors requires organizations to focus on marketing and consumer-facing departments and to examine whether these departments' databases or, more abstractly, the organizations' taken-for-granted understanding about whom they have served and should serve and why, carry entrenched social and racial biases.

Organizations must thus focus on learning about the specific biases that might be present in their own algorithms and processes to root them out. In the United States, the Algorithmic Accountability Act of 2019 would require companies to assess their AI systems for "risks of 'inaccurate, unfair, biased, or discriminatory decisions' and to 'reasonably address' the results of their assessments" (MacCarthy 2019, p. 1). Rather than reacting to a changing regulatory landscape, firms should proactively collaborate with technology experts and thought leaders in computer science, sociology, and psychology to develop and conduct such audits. Firms can then share both their audit processes and outcomes, for example by engaging in lobbying efforts to ensure that regulations passed in the name of consumer welfare include meaningful and technologically appropriate provisions to protect consumers from discrimination.

Experience design. Organizational learning should be leveraged in the design phase to develop AI classification experiences that minimize consumers' likelihood of feeling misunderstood. Managers could build on the insights gained from listening to consumers who felt they were classified on the basis of narrowly defined identities to experiment with diversifying and broadening the content they provide and to propose products that are dissimilar from the user's preference profile. Indeed, Spotify has launched Taste Breakers, a function that introduces customers to music to which they normally do not listen. Similar attempts at "bursting the bubble" are especially important in light of the possibility that, by optimizing information provision on the basis of past choices, AI both ignores long-term goals that do not reflect short-term behaviors (André et al. 2018) and increases attitude extremity and polarization (Flaxman, Goel, and Gao 2016). Firms could also address feelings of being misunderstood by asking consumers to validate AI-based inferences. As greater user participation in the implementation of algorithms increases satisfaction in decision support systems (Wierenga and Oude Ophuis 1997), periodically offering consumers the opportunity to update the AI's view of the self could similarly reduce potential frustration.

Managers can build on the insights gained from listening to discriminated consumers to design both debiased and antibias AI experiences that foster an inclusive society rather than perpetuate inequality (Green and Viljoen 2020). To do so, managers should institute protocols that swiftly react to any bias uncovered in regular audits of the AI systems for the presence of discrimination (Zou and Schiebinger 2019). Organizations should also diversify their hiring to include more members of social minority groups and ensure that their culture and processes represent diverse viewpoints at all stages of the design of AI classification experiences. For example, advocates for reducing bias in AI have suggested that technology companies must employ more individuals with disabilities to learn how to eliminate disability bias from AI (Clegg 2020). The tension between feeling understood and misunderstood in classification experiences represents a learning opportunity not only for managers but also for researchers.

Future Research on the AI Classification Experience

Sociological research questions. Researchers can unpack the influence of sociocultural factors on classification experiences. Values and ideology may change consumers' interpretation of personalized predictions, as those who are more aware of the sociohistorical context of discrimination by algorithm (Noble 2018) and belong to marginalized groups should also feel more vulnerable to AI's potential to restrict access to resources and freedom (RQB1).

Drawing on research that examines the ways in which powerful institutions define the consumer (Borgerson 2005), future work should also explore the social classifications that firms routinely inscribe into their AI solutions, such as certain consumers' habits, norms, and preferences. This lens can usefully unearth the existence of ideological blind spots in the models employed by firms and examine the uneven landscapes of experiences and choices that these models produce when consumers are subjected to them (RQB2).

Psychological research questions. Future research should explore how psychological processes affect the extent to which consumers feel misunderstood in classification experiences. Open questions concern lay beliefs about how organizations create AI classifications (RQB3) and whether certain inferred categorizations are especially likely to induce feelings of being misunderstood (RQB4). For example, research on attributional ambiguity suggests that stigmatized consumers may attribute AI classifications to bias toward their group identity on the part of the algorithm rather than to other causes (Crocker and Major 1989).

More generally, feeling misunderstood may be more likely in contexts where consumers value uniqueness over belongingness (RQB5). For example, patients are reluctant to use medical AI due to a sense that it cannot account for their unique characteristics and circumstances as well as human doctors can (Longoni, Bonezzi, and Morewedge 2019). The nature of a task may also have an influence (RQB6): Consumers tend to exhibit greater aversion toward algorithms for subjective tasks, which are based on personal opinions or intuitions, than for objective ones, which are based on quantifiable and measurable facts (Castelo, Bos, and Lehman 2019). Given that many AI systems learn and predict subjective taste, negative reactions to inferred classification might be especially common.

The AI Delegation Experience

A "delegation experience" is one in which consumers involve an AI solution in a production process to perform tasks they would have otherwise performed themselves. These tasks can be decisions, such as when Google Assistant, at the consumer's request, calls a hairdresser, matches the consumer and the hairdresser's calendars, and uses a human-like voice to book an appointment. They can also be actions in the digital world, like those performed by Smart Compose, a writing tool that uses AI to help consumers write emails. Finally, they can be actions in the physical world, such as when the Nest Thermostat learns the consumer's temperature preferences and programs itself to fit them.

By not having to engage in the tasks the AI performs on their behalf, consumers in delegation experiences can feel empowered in two distinct ways. First, consumers can spend their time and effort on activities they find more satisfactory and meaningful: they can work less and enjoy the positive effects of leisure (Fishbach and Choi 2012), or they can work better and enjoy greater happiness by delegating extrinsically motivated tasks to AI and keeping intrinsically motivated tasks for themselves (Botti and McGill 2011). Second, consumers can focus on activities that are more suitable to their skills and leave to AI those on which they underperform. This way, they can enhance self-efficacy, or the perceived ability to master the environment to produce a desired outcome (Bandura 1977).

Given the empowering benefits of delegation experiences, managers may be tempted to offer consumers increasingly more opportunities to delegate tasks to AI. However, like the case in which the mere presence of too many choice options can reduce consumers' satisfaction (Iyengar and Lepper 2000), the mere presence of too many delegation opportunities may lead to aversive consequences. We next examine this tension between the possibility of AI to both empower and replace consumers both at the societal and individual level.

Sociological Context: The Transhumanist Narrative

To analyze the negative aspects of delegation brought about by the possibility of being replaced from a sociological perspective, it is helpful to examine how the heuristics that have guided consumers' interactions with AI tools have been historically understood in popular culture. We draw on widespread science fiction and social science literature that falls into the so-called "transhumanist" genre. From Fritz Lang's *Metropolis* to Isaac Asimov's *I, Robot*, and from Mary Shelley's Gothic *Frankenstein* to James Cameron's *Terminator*, countless cautionary tales have profiled the dangers of reimagining human capabilities and characteristics through a technological mirror. Specifically, these stories fuel the view that, by transcending human limitations, technology eventually molds into an omnipotent superhuman and subsequently constitutes the ideal of technological perfection—implying new standards.

Critics of this transhumanist perspective (Sassen 2014, p. 23) have linked AI to "new logics of expulsion" and economic redundancy that arise as AI approaches aging, health, productivity, and other domains through the transhumanist lens of limitless performance rather than standard levels of well-being or productivity. These observers fear that AI solutions will result in significant unemployment, leading to a rapid increase in surplus populations whose AI experience will be their de facto removal from the productive aspects of the social world.

In the social science literature, this superhuman narrative is paralleled in the Computers Are Social Actors and Human Computer Interactions paradigms, according to which the same heuristics used for human interactions are mindlessly applied to computers (Grudin 2017; Nass and Moon 2000). Since the 1960s, technology companies have periodically imbued the productive aspects of AI technology and machine prototypes with mythic narratives emphasizing that science and technology will eventually accomplish human immortality.

These transhumanist ideas, which emphasize technological progress as an unstoppable force that alters human experience (Hayles 1999), have been deeply inscribed in contemporary AI experiences, from the promise that the Roomba vacuum cleaner could perform tasks more effectively than humans to the promise that 23andMe could help in the creation of genetically optimized offspring. However, the transhumanist preoccupation with Promethean aims underlying many contemporary AI experiences also leads to systemic dehumanization (Fukuyama 2002; Habermas 2003). For instance, human perception of mastery over the environment depends on not being subject to unilaterally imposed specifications. A world in which our interactions with machines are fueled by transhumanist ideals will endorse a glorification of capitalism's endless creativity while treating destructiveness and human replacement as normal costs of doing business (Schumpeter 1942). Furthermore, an economic obsession with "perfection," "progress," and "efficiency" will promote the rise of the "useless class" (Harari 2017), individuals whose skills are no longer developed or demanded, thus fundamentally eroding democracy and social justice.

Psychological Perspective: The Replaced Consumer

Delegation experiences can help consumers feel empowered but can also raise concerns about being replaced. The mere recognition of AI's capability to act as a substitute for human labor can be psychologically threatening for three main reasons. First, people have a strong desire to attribute consumption outcomes to one's own skills and effort (Bandura 1977; Leung, Paolacci, and Puntoni 2018). Research on human–computer interaction has shown that humans often see computers as disempowering because they deprive humans of the sense of accomplishment related to an activity, so much so that humans tend to credit themselves for positive outcomes and blame computers for negative ones (Moon and Nass 1998). In contexts where products are crucial to the experience of having an identity as a certain type of person (Reed et al. 2012), delegation experiences may feel tantamount to cheating. In the fishing industry, for example, AI can help anglers be more effective in location and bait decisions. However, in the words of biologist Culum Brown:

> It is really getting kind of unfair. If you are going to use GPS to take you to a location, sonar to identify the fish and a lure which reflects light that humans can't even see, you may as well just go to McDonald's and order a fish sandwich. (*The Economist* 2012)

Second, outsourcing labor to machines prevents consumers from practicing and improving their skills, which can negatively influence self-worth and contribute to a satisficing tendency by which individuals settle for a level of engagement that is just good enough. Consider the experience of journalist John Seabrook. While composing an email to his son, Seabrook started the sentence "I am p . . . ," intending to write "I am pleased," but resolved to instead accept the suggestion of Google's Smart Compose "I am proud of you." After hitting Tab to accept the suggestion, Seabrook (2019) muses:

> What have I done? Had my computer become my co-writer? That's one small step forward for artificial intelligence, but was it also one step backward for my own? . . . I'd always finished my thought by typing the sentence to a full stop, as though I were defending humanity's exclusive right to writing, an ability unique to our species. I will gladly let Google predict the fastest route from Brooklyn to Boston, but if I allowed its algorithms to navigate to the end of my sentences how long would it be before the machine started thinking for me?

Finally, outsourcing tasks to AI can lead consumers to experience a loss of self-efficacy. Self-efficacy is an antecedent of personal control (Bandura 1977), and it is heightened when individuals are actively engaged in creative tasks (Dahl and Moreau 2007; Norton, Mochon, and Ariely 2012). The notion that being productive is a way to feel in control is consistent with findings showing that consumers who experience low control attempt to reestablish it by choosing products that require higher, versus lower, effort to achieve a desired outcome (Cutright and Samper 2014). In line with this view that delegation can lead to loss of control, drivers involved in GPS-related accidents tend to describe their experience in terms of surrendering control to the machine. Take for instance the tourists who drove their car into the ocean trying to reach an Australian island and recounted that the GPS "told us we could drive down there . . . It kept saying it would navigate us to a road" (Milner 2016).

The tension between being empowered and replaced is relevant from a managerial perspective because AI designers need to decide how delegation experiences should be designed to protect self-efficacy and self-identity. We next discuss potential recommendations emerging from the sociological and psychological analysis of this tension.

Managerial Recommendations: Understanding the Replaced Consumer

Organizational learning. Companies can start by learning how to integrate the human desire for self-efficacy into corporate discourse in two main ways. First, they can collaborate with family scholars, workplace psychologists, and health sociologists to understand the consequences of human replacement by AI. Second, they can engage in conversations with consumers to gain greater insight into which activities they prefer to reserve for themselves versus delegate to AI, and how these preferences shift across consumer, identity, and task. Organizational design and personnel policies can facilitate this learning by ensuring that the insights gained through external collaborations and consumer listening permeate the firm's culture, especially in the more technical functions. For instance, technology firms could hire experts in creativity such as artists, artisans, or chefs into AI-focused experience design roles.

Firms could also learn from organizations that protect, support, and enhance abilities that are conceived as intrinsically "human" and on which individuals remain superior to machines, such as performing complex tasks, adapting to changes, using emotional intelligence, and offering nuanced judgments in unstructured environments (Hume 2018). Thus, collaborations with museums, theaters, and universities' humanities departments can inspire managers to understand how AI can preserve, rather than subvert, traditional human values such as creativity, collaboration, and community (Brunk, Giesler, and Hartmann 2017).

Experience design. The learning achieved in the previous phase should serve as the bedrock on which AI designers decide how to model delegation experiences to protect self-efficacy and self-identity (Leung, Paolacci, and Puntoni 2018). Division of labor in production processes can have positive effects on demand if consumers feel they have the competence to make sound decisions about the tasks in which they decide to engage (Fuchs, Prandelli, and Schreier 2010). Thus, AI can be conceived as a platform to enhance intrinsically human skills and values. In the medical domain, for example, the benefits of AI-powered surgical robots for consumers depend on the way in which the surgeon's input and supervision is designed. Surgical robots are more precise than humans, can make quicker and more reliable diagnoses, and are more democratic and cost-efficient than current systems because they can intervene outside of hospitals. Still, the structure of surgeons' supervision of the robots is central to the success of this technology, both because patients are afraid of being operated on by a machine and because the AI cannot yet outperform human doctors in some critical technical and social skills (Max 2019).

Given the link between self-efficacy and control, the design of delegation experiences could also consider the extent to which consumers make choices and initiate actions (Carmon et al. 2020; Schmitt 2019). For example, autonomous vehicles should allow consumers to customize peripheral features to avoid perception of a lack of control (André et al. 2018), and digital assistants in computer games should not be anthropomorphized to preserve players' sense of autonomy (Kim, Chen, and Zhang 2016). The classic finding that cracking fresh eggs into a premade Betty Crocker cake mix might be enough to reestablish consumers' self-worth and improve adoption (Marks 2005) still resonates in the context of AI, as the amount of control needed by consumers to reduce a self-efficacy threat can be quite small. For instance, offering users the possibility to correct an algorithm's output, even if only slightly, is enough to increase their likelihood of using the superior, although imperfect, algorithm rather than the preferred, inferior human forecast (Dietvorst, Simmons, and Massey 2016).

Future Research on the AI Delegation Experience

Sociological research questions. The extent to which consumers feel replaced by AI is likely shaped by cultural narratives about AI and by the shared understanding of what it means to be productive. Activities that tend to be perceived as if they ought to fall to human skills and competence (Castelo, Bos, and Lehman 2019) should be more likely to spur feelings of being replaced (RQC1). Consider a self-driving car choosing between stopping and crossing at an intersection versus choosing between swerving and killing one pedestrian or not swerving and killing several pedestrians (Bonnefon, Shariff, and Rahwan 2016): the car's passenger may feel more replaced in the latter case, which involves a moral dilemma, than in the former case, which involves a mechanical decision. Furthermore, feeling replaced by AI may alter the social or moral acceptability of behavior and its likelihood of occurrence (RQC2). For example, self-protective behaviors appear more moral when adopted by autonomous vehicles than by humans (Gill 2020). Perceptions of what ought to fall to human competence may, however, shift rapidly as AI technology advances (RQC3).

Negative reactions to feeling replaced by AI are likely to differ across consumption contexts (RQC4). Future research can explore whether delegation to AI is less threatening in categories where consumers are already familiar with recommendation agents (e.g., entertainment), are less confident in their own preferences (e.g., finance), are open to experimentation (e.g., food), and can trust the AI brand (JWT Intelligence Wunderman Thompson 2016). As AI encroaches on an ever-expanding set of human activities, researchers could also explore whether feelings of replacement in one domain could motivate consumers to seek control in others (RQC5). For example, will consumers engaged in daily delegation experiences become more controlling in nonconsumption domains, such as politics?

Psychological research questions. Future research should examine when the psychological processes that lead to the experience of feeling replaced by AI are activated, as well as the consequences of such feelings. For example, is the extent to which individuals perceive delegation experiences as a threat to the self a function of whether consumption is motivated by instrumental or symbolic motives (RQC6)? Preferences for human over robotic labor tend to be stronger in symbolic consumption contexts (Granulo, Fuchs, and Puntoni 2020), and the same might apply in the case of one's own labor: whereas for most consumers, being replaced by Nest in setting their home's temperature is likely perceived as desirable, for those whose identity is tightly linked to housekeeping, this replacement may be seen as aversive (Leung, Paolacci, and Puntoni 2018). A related topic pertains to how a focus on the outcome or on the process differently influences perceptions of delegation experiences (RQC7). Products are means to ends, but the process of consumption, as well as the performative display of skill and knowledge, can often be intrinsically valuable to consumers (Reed et al., 2012). For example, for a person who is nurturing an angler's image, the extent to which AI-driven fishing tools are seen as self-threatening may depend on the reference group's norms about task delegation and the relative importance placed on the outcome (e.g., a bigger catch) or the process (e.g., finding a good location for fishing).

When self-efficacy and control are threatened in delegation experiences, consumers may employ different strategies to restore them, including increasing agency and seeking structure and boundaries (Landau, Kay, Whitson 2015). Thus, future research can explore whether and when consumers who feel replaced opt to constrain the involvement of the AI in production processes (RQC8) to both reaffirm self-efficacy by increasing their own role in these processes and seek structure by physically and/or mentally bounding AI features. This deliberate limitation of the AI is similar to situations in which consumers restrict their experience with smart objects to the most basic and least innovative forms of interaction (Hoffman and Novak 2018).

The AI Social Experience

AI's capability for engaging in reciprocal communication produces what we term a "social experience." We focus on two types of social experiences: when consumers know at the outset that the interaction partner is an AI, such as when using a voice assistant like Apple's Siri, and when they interact with an AI representing an organization without necessarily knowing initially that it is nonhuman, such as when receiving customer service from an automated chatbot. In both cases, consumers have a social interaction with AI as part of a consumption experience in which the end goal is not the AI interaction. We do not focus on two other types of interactions: when consumers are never aware that the interaction partner is a simulated person (because the experience would be perceived as a normal social interaction) and when consumers interact with the AI as an end in itself, as in the case of a robotic pet.

Social experiences are beneficial when consumers can find in AI a vehicle for information exchange that connects them with the firm in a natural way. This often happens when anthropomorphic features are incorporated in AI-enabled products: anthropomorphic cues increase trust toward self-driving cars (Waytz, Heafner, and Epley 2014) and reduce perceived risk when consumers are in a position of power (Kim and McGill 2011), as when they interact with a virtual assistant. More generally, developments in social robotics are making it possible to create comfortable and even emotionally meaningful AI-powered service interactions (Van Doorn et al. 2017). Social AI experiences are beneficial also because they can be more efficient, especially in situations where the alternative to AI is not a human interaction but the absence of any interaction: AI provides consumers access to firms through "conversational commerce."

Despite these advantages, social experiences may also alienate consumers. Negative consumer reactions to simulated social interactions can go well beyond the occasional disappointment as these interactions emerge in a rich cultural context where they can easily trigger societal and individual concerns with unbalanced intergroup relations and discrimination.

Sociological Context: Humanized AI Narrative

The sociological starting point for social experiences is the widespread cultural fascination with humanized machines (Adam 1998; Haraway 1985; Suchman, Roberts, and Hird 2011), specifically, the preference for machines that emulate the human body and traits. For instance, a well-noted trope in science fiction is the pursuit of the perfect artificial woman (Hayter 2017), a male fantasy of a beguiling, seductive, and sexually obliging object (Rose 2015). These female robots or "gynoids" are routinely imagined as "basic pleasure models" in Philip K. Dick's *Blade Runner* and sex workers in Michael Crichton's *Westworld*, or they are traded like used cars in Steve de Jarnatt's *Cherry 2000*.

This cultural preference for humanized AI is amplified by the widespread use of anthropomorphized chatbots and voice assistants in contemporary AI markets. Humans are less open, agreeable, conscientious, and self-disclosing when they interact with AI versus humans (Mou and Xu 2017). However, these perceptual barriers can be overcome, and intimate experiences can be accomplished, when AI products feature human characteristics, behaviors, and language, thus ultimately becoming "artificial besties."

Nevertheless, in this narrative, AI companies that strive for greater human touch cannot ignore that AI products and services modeled as "obliging, docile, and eager-to-please [human] helpers" often contribute to the social alienation of particular groups in society (West, Kraut, and Chew 2019, p. 104). Consistent with this finding, from the iconic robot character Maria in *Metropolis* to Apple's Siri, patriarchal norms and preferences embedded in seemingly benign AI experiences have the potential to engage only certain types of users, such as white men, while alienating others, such as women and racial minorities (Adam 1998; Hayles 1999; Haraway 1985).

From this perspective, an instance such as Siri's earlier programming to answer to users who say, "you're a slut" with "I'd blush if I could" (Rawlinson 2019) would not just be evidence of biases within the male-centric technology sectors and of the fact that AI mirrors the misogyny concealed in language patterns but also diagnostic of the tendency to undermine AI's social and inclusive possibilities. By collapsing dualistic categories such as male versus female, for instance, social experiences could at least partially ease the social isolation brought about by misogynous and racial stereotyping. At the same time, because anthropomorphized AI typically reproduces such dualistic categories to maximize consumer engagement (e.g., men who treat women as assistants, women who are more assistant-like), social experiences have the potential to exclude rather than include and to alienate rather than connect certain groups of consumers.

Psychological Perspective: The Alienated Consumer

AI social experiences have the power to bolster consumer–firm relationships but also to alienate consumers. We identify two main types of alienation engendered by AI social experiences. The first type can occur with any failed automated customer service, as exemplified in this exchange between a customer and chatbot, UX Bear (Wong 2019):

> Bot: "How would you describe the term 'bot' to your grandma?"
> User: "My grandma is dead."
> Bot: "Alright! Thanks for your feedback. [Thumbs up emoji]"

This type of alienation may explain consumers' widespread resistance to replacing humans with machines (Castelo, Bos, and Lehman 2019; Leung, Paolacci, and Puntoni 2018). For example, consumers report feelings of discomfort when interacting with "social robots" in service contexts (Mende et al. 2019), and customers' responses in a field study became markedly more negative when they were informed in advance that their interaction partner would not be a human (Luo et al. 2019). The potential of AI to trigger alienation is also evident in the resurgent interest in social connections that are unmediated by technology, such as authentic consumption experiences (Beverland and Farrely 2010) and more personal marketing exchanges (Van Osselaer et al. 2020).

The second type of alienation results from AI's failure to interact successfully with specific groups of consumers. For example, the UK government's reliance on AI to handle claims to its social security program led to experiences like that of Danny Brice, who has learning disabilities and dyslexia and describes his attempts to use the automated Universal Credit program as follows (Booth 2019):

> I call it the black hole . . . . I feel shaky. I get stressed about it. This is the worst system in my lifetime. They assess you as a number not a person. Talking is the way forward, not a bloody computer. I feel like the computer is controlling me instead of a person. It's terrifying.

Thus, AI can exacerbate existing barriers that prevent specific social groups from accessing essential social services, reinforcing societal inequity. Another example of how alienating social experiences can feed inequality is chatbots programmed without considering how existing discrimination in society may affect their operation, such as when Tay, a Twitter bot created by Microsoft, began offering white supremacist answers to users soon after its launch, with exchanges like the following (Me.me 2020):

> User: "What race is the most evil to you?"
>
> Bot: "Mexican and black."

The cultural narratives of oppression and discrimination underlying this example are even more apparent in the context of personal virtual assistants. Journalist Sigal Samuel recounts working on a piece about sexist AI (Samuel 2019b):

> I said into my phone: "Siri, you're ugly." She replied, "I am?" I said, "Siri, you're fat." She replied, "It must be all the chocolate." I felt mortified for both of us. Even though I know Siri has no feelings, I couldn't help apologizing: "Don't worry, Siri. This is just research for an article I'm writing!" She replied, "What, me, worry?"

Alienating social experiences such as this, in which women face societal pressures around their appearance, may lead consumers to denigrate and belittle the AI, similarly to situations in which individuals derogate outgroup members to reaffirm self-esteem following an identity threat (Branscombe and Wann 1994). Dissatisfaction with a voice-enabled device might produce verbal responses that emphasize its artificial and worthless nature. The tendency to objectify others, and women in particular, is well-known (Fredrickson and Robert 1997), and it should be stronger when the interaction partner is, in fact, an inanimate entity, however human-like its communication. Indeed, conversational failures lead consumers to express more frustration with AI when it has a female rather than a male voice (Hadi et al. 2020). Firms risk translating this denigration of AI into behaviors that reinforce inequality. As technology enables companies to create automated interactions that are more and more like real human interactions, a new set of ethical issues confront both organizations and marketing researchers, as we discuss in the next sections.

Managerial Recommendations: Understanding the Alienated Consumer

Organizational learning. To effectively manage AI social experiences, companies should learn how to acknowledge and accommodate the heterogeneity of human interaction styles and needs. To this aim, firms should collect information directly from consumers who have experienced alienation in their interactions with AI. In addition, firms can leverage technology to gauge and measure alienation (operationalized using measures like amount of stress in the customer's voice) in chats with AI service providers to develop generalizable insights about when alienation is most likely to occur. Firms should also interact with psychologists, sociologists, gerontologists, and other experts to learn about both causes and consequences of alienation.

Organizational learning should also ensure that definitions of anthropomorphism do not draw on and calcify harmful stereotypes about social categories and the way they interact. One way to do so is breaking with organizational cultural conventions that idealize AI as a passive and subservient humanized other by involving experts like linguists, critical theorists, and social psychologists who study the subtle ways in which stereotyping affects communication. For example, disseminating information throughout an organization about the potential societal consequences of exposure to subservient female AIs may shift AI designers away from using female names and voices as defaults (Teich 2020).

Experience design. Using the greater sensitivity emerging from organizational learning activities, firms can improve the design of AI social experiences. As timely and appropriate firm responses can do much to mitigate the harmful consequences of service failure (Hart, Heskett, and Sasser 1990), firms should work to increase the effectiveness of interactive AI applications to minimize the likelihood of alienation. Research shows that consumers respond positively when AI service providers personalize the interactions, for example by using the customer's name and explaining the reasons for malfunctions (Carmon et al. 2020). Relatedly, firms should also ensure easy and swift transitions from AI to human representatives when the interaction becomes difficult or aversive.

To avoid the perpetuation of harmful stereotypes, companies could also strive to develop AI that is less, rather than more, humanlike (Hadi et al. 2020), and indeed, software developers have begun investigating the creation of gender-neutral voices (Sydell 2018). This requires a radical change in the mindset of many AI designers (and marketing academics), who often take it for granted that anthropomorphism fosters better relationships with customers (Kim, Chen, and Zhang 2016). Organizations should also evaluate the potential consequences of using AI for access to basic social services for consumers like Danny. When AI is deployed to provide important welfare services, designers need to recognize the barriers that they can create for specific user groups, even when the technology has satisfied standard performance benchmarks.

Finally, instead of worrying solely about designing to improve human–AI interaction, firms could address alienation by considering how AI design can improve human–human interaction. Firms can design social experiences that help support what Epp and Velagaleti (2014) call "care assemblages" by connecting individuals to dear ones in ways that are reminiscent of popular social media strategies designed to foster and satisfy consumers' social goals (Epp, Schau, and Price 2014). Thus, companies could actively shift from understanding AI as a substitute for humans toward understanding AI as an interface that facilitates social connection (Farooq and Grudin 2016).

Future Research on the AI Social Experience

Sociological research questions. Consumers vary in the extent to which they hold antibias beliefs and are willing to take action to address bias in society (Ivarsflaten, Blinder, and Ford 2010). Those who are more concerned about AI fostering alienation may be particularly likely to reject the idea that AI can be a true social partner (RQD1). Cultural differences are also likely to influence the extent to which consumers perceive social experiences with AI as alienating (RQD2). Asian consumers feel a stronger connection to both people and things than Western consumers and, as a result, have shaped their social interactions with AI in more personal ways: whereas AI social experiences in the West are mainly utilitarian and involve disembodied personal assistants, those in the East involve human and animal-appearing robots that are assumed to serve and improve society (Belk, Humayun, and Gopaldas 2020).

If, over time, AI social experiences become commonplace, future research should explore their broader interpersonal and societal consequences (RQD3). Just as the synthetic and unrealistic nature of pornography has been accused of distorting teens' sexual expectations (Owens et al. 2012), AI social experiences might increase the prevalence of sexist language if they trigger female objectification (Hadi et al. 2020). Researchers could also build on literature on intergroup relations, such as Haslam's (2006) theory of dehumanization, to investigate the conditions under which objectification of AI is more likely to occur (RQD4).

Psychological research questions. An information processing perspective could shed light on how AI social experiences are interpreted and evaluated. The timing of disclosure that the interaction partner is, in fact, an algorithm may influence consumer response to social experiences (Luo et al. 2019), similarly to the "change of meaning" that occurs when consumers realize that a message is meant to influence their behavior (Friestad and Wright 1994). Thus, alienation might be more likely to emerge if consumers question the company's intention behind disclosing the nature of the interaction partner (RQD5). Moreover, research on the effects of disclosure on word of mouth (Tuk et al. 2009) and product placement (Campbell, Mohr, and Verlegh 2013) shows that situational factors may influence consumer reactions through an effect on cognitive capacity, and researchers can examine how these factors also affect alienation (RQD6).

Future research could also explore the role of brand equity (RQD7). As brand attachment influences consumer expectations and can shield companies from negative appraisals in ambiguous situations (Lee, Frederick, and Ariely 2006), stronger consumer–brand relationships may also insulate consumers from experiencing interactions with AI as alienating.

Agenda for Future Research on Consumers and AI

We developed a framework to structure our understanding of consumers' interaction with AI by defining and contextualizing the AI data capture, classification, delegation, and social experiences using both sociological and psychological lenses. In this final section, we go beyond these four experiences to identify additional future research questions in two areas: interrelationships between the four experiences and new AI experiences that may emerge along with new capabilities. These additional research questions are also included in Table 1.

Interrelationships Between Experiences

Although we discussed the four consumer AI experiences separately, our framework is not intended to suggest that they exist independently. On the contrary, these experiences could be seen as different aspects of the same customer journey and, as such, could influence each other (Lemon and Verhoef 2016). An important avenue for future research is to explore where and how consumers' experience with one AI capability directly affects their experience with another AI capability (Giesler and Fischer 2018). For example, whether consumers feel served versus exploited in an AI data capture experience is likely to affect a subsequent AI classification experience. Consumers who feel exploited may be more likely to worry about AI inappropriately using their personal data to regulate access to valued resources (RQE1). Similarly, intrusive data capture requests might foster consumer alienation (RQE2). For instance, students who view an AI-enabled teaching assistant such as Packback.co as overly inquisitive might feel less included in the virtual classroom and less likely to participate in communal activities such as online discussion boards. Future research can also explore whether consumers are more likely to perceive an AI classification as benefiting them when they are asked to validate inferences made by the AI, turning a classification experience into a delegation one (RQE3).

Another avenue for research is related to the identification of additional ways in which AI experiences influence each other by uncovering shared theoretical foundations. For instance, the data capture and delegation experiences share an emphasis on concerns about personal control, as interacting with AI often involves giving up at least some control over personal data and production processes (RQE4). Similarly, classification and social experiences share an emphasis on concerns about self-identity, as interacting with AI often influences inferences about how AI understands the self and feelings of belonging (RQE5). Confirming the relevance of these theoretical perspectives, personal control and self-identity have been recognized as key concerns in the nascent literature on consumer AI (André et al. 2018; Belk, Humayun, and Gopaldas 2020; Carmon et al. 2020; Schmitt 2019). A search for shared theoretical foundations may stimulate academic research and help AI designers form a more holistic understanding of consumers' interaction with AI. For example, as consumers come to understand AI as an independent intelligence operating in the marketplace to whom they can delegate tasks and with whom they can interact, marketplace metacognition and social intelligence (Wright 2002) theory can be leveraged to better understand the theories consumers have about how AI "thinks" (its intentions, strategies, etc.) and how these lay theories influence how consumers respond to AI.

An integrated view of the four experiences will also maximize the value consumers see in organizations' investments into AI. Some companies find themselves in a catch-22 situation in which users need to reveal personally sensitive information for the company to provide valuable benefits but are unwilling to do so unless they can first experience such benefits (Grafanaki 2017). Drawing on an integrated understanding of AI consumer experiences, it may be possible to articulate and structure alternative customer journeys. For example, companies could provide an initial basic service requiring limited disclosure of personal information and later offer the possibility to access an upgraded version that requires additional individual data. Thus, demands for data capture could ramp up as the company is able to demonstrate the benefits that delegation brings to consumers (RQE6).

Unchartered AI Experiences

Our framework offers a parsimonious template to conceptualize how consumers navigate the disparate consumption contexts powered by AI, including social media, online shopping, and personal virtual assistants. In doing so, the framework identifies experiences relevant to a large variety of industries and products. However, additional consumer experiences that we did not examine are on the rise in specific industry sectors, and future research can examine both industry-specific experiences stemming from existing capabilities and new experiences stemming from emerging capabilities (Figure 1).

Although we theorized the production capability as leading to a delegation experience, this capability can also be used to develop an AI "learning experience" in the education industry. Educators can facilitate knowledge and skill acquisition by letting AI personalize aspects of the learning process, such as producing tailored content and testing materials. Future research can examine how different aspects of the learning experience affect subjective and objective assessments of educational outcomes (RQF1). For example, the risk of engendering negative feelings of being replaced in delegation experiences may have a parallel in learning experiences: If an AI application makes it more challenging to internalize the outcome of the learning process, learning experiences might decrease satisfaction and motivation. This may be especially likely to occur when the learning content is relevant to one's identity: just like consumers tend to resist automation in identity-relevant consumption domains when it prevents the internal attribution of consumption outcomes (Leung, Paolacci, and Puntoni 2018), students may show reactance to AI applications that prevent them from attributing learning to their own talent and effort (RQF2).

Another avenue for future research would be to relax some of our definitional boundaries to include a larger set of consumption contexts. For example, in our discussion of social experiences, we explicitly excluded contexts in which the interaction with AI is the end in itself, such as sex robots and robotic pets, which are increasingly important in the entertainment and health care industries. Such applications of AI's communication capability give rise to an AI "companionship experience" (RQF3). On the one hand, AI companionship experiences are positive because they can provide both cognitive and socio-emotional benefits (Broadbent 2017). On the other hand, they can deceive vulnerable consumers such as the elderly and toddlers into believing the AI has feelings and may be used as substitutes for real human connections (Van Oost and Reed 2010). While the goal of the creation of robot companions is to simulate an interaction with a real living being, future research could explore at what point the potential for deception and substitution becomes damaging (RQF4).

Finally, emerging AI capabilities may create new consumer AI experiences. In the health care sector, nanorobots are being developed to bring AI solutions directly inside the body, and smartphones, fitness trackers, and smart watches provide essential extensions of cognitive and perceptual capabilities. These products give rise to what researchers have called an AI "cyborg experience" (Giesler and Venkatesh 2005). A cyborg is "a cybernetic organism, a fusion of the organic and the technical forged in particular, historical, cultural practices" (Haraway 1985, p. 51). Thus, cyborg experiences emphasize hybridity, self-enhancement, and often radical self-modification, requiring future research to reexamine longstanding epistemic boundaries between human and machine (Belk 2019). On the one hand, cyborg experiences destabilize human autonomy and control and might fundamentally undermine consumer freedom (Wertenbroch et al. 2020). On the other hand, they collapse dualistic categories like man and machine and might promote consumer empowerment and the circumvention of structural inequalities (RQF5). Lastly, cyborg experiences also raise mind-bending but nonetheless intriguing questions about the kinds of consumption experiences that an AI itself might have (Hoffman and Novak 2018). Consider, in this context, that many firms selling on Amazon today no longer market their offerings directly to consumers but to Amazon-controlled algorithms that act on behalf of these consumers. Future research could explore what marketing strategies are most effective when AI is marketing to AI (RQF6).

Conclusions

AI-enabled products promise to make consumers happier, healthier, and more efficient. Consumer-facing AI products and services such as college admissions software, chatbots, and knowledge aggregators have been heralded as forces for good that can make important contributions to problems such as poverty, lack of education, chronic illness, and racial discrimination. For instance, a World Economic Forum discussion on the future of AI argued that "no one will be left behind" (Zhou 2020). A key problem with these optimistic celebrations that view AI's alleged accuracy and efficiency as automatic promoters of democracy and human inclusion is their tendency to efface intersectional complexities.

Instead of considering algorithms as neutral tools, AI designers should recognize that their interventions are "inherently political" and interrogate themselves on "the relationship between their design choices, their professional role, and their vision of the good" (Green and Viljoen 2020, p. 26). We hope that our formulation serves as an antidote to the temptation of "technological solutionism" (Morozov 2013) and a useful guide to contrast cases in which targeted consumer segments are subjected to biased outcomes as a result of uncritical firm reliance on AI. We therefore end by noting a key role for the American Marketing Association in shaping the way marketers think about using AI ethically. Although some organizations are beginning to create ethical guidelines around AI, such as the Organization for Economic Co-operation and Development's "Principles for AI" (Organisation for Economic Co-operation and Development 2020) and the European Commission's "Ethics Guidelines for Trustworthy AI" (European Commission 2020), they are not specifically for marketers. The code of conduct of the American Marketing Association currently includes no mention of AI. We recommend the formation of a taskforce of practitioners and academics from different disciplines to evaluate how professional guidelines could acknowledge the new ethical challenges raised for marketers by the growth of AI.

Acknowledgments

The authors thank Carl Mela and the Marketing Science Institute for organizing the 2018 MSI Scholars conference that provided the opportunity to work together on this project, Christine Moorman and John Deighton for their guidance, participants at the Marketing Science conference in Rome for their feedback, and Gizem Yalcin for her help and feedback.

Author Contributions

Order of authorship was determined by random draw; all authors contributed equally.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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