+Model
RETAIL-801; No. of Pages 15
ARTICLE IN PRESS

Journal of Retailing xxx (xxx, xxxx) xxx–xxx

Journal of Retailing

A Framework for Collaborative Artificial Intelligence in Marketing☆

Ming-Hui Huang [a,*], Roland T. Rust [b]

[a] Department of Information Management, College of Management, National Taiwan University, 1, Sec. 4, Roosevelt Rd., Taipei 10617, Taiwan
[b] Robert H. Smith School of Business, University of Maryland, 3451 Van Munching Hall, College Park, MD 20742, United States

Abstract

We develop a conceptual framework for collaborative artificial intelligence (AI) in marketing, providing systematic guidance for how human marketers and consumers can team up with AI, which has profound implications for retailing, which is the interface between marketers and consumers. Drawing from the multiple intelligences view that AI advances from mechanical, to thinking, to feeling intelligence (based on how difficult for AI to mimic human intelligences), the framework posits that collaboration between AI and HI (human marketers and consumers) can be achieved by 1) recognizing the respective strengths of AI and HI, 2) having lower-level AI augmenting higher-level HI, and 3) moving HI to a higher intelligence level when AI automates the lower level. Implications for marketers, consumers, and researchers are derived. Marketers should optimize the mix and timing of AI-HI marketing team, consumers should understand the complementarity between AI and HI strengths for informed consumption decisions, and researchers can investigate innovative approaches to and boundary conditions of collaborative intelligence.

Keywords: Artificial intelligence; Collaborative AI; Collaborative intelligence; Augmentation; Replacement

Introduction

In recent years, AI has moved retailing forward in many ways, such as making big data available for prediction, facilitating more informed retail and consumption decisions, enabling visual display and merchandise, and creating customer engagement (Grewal, Roggeveen, and Nordfalt 2017). AI also is rapidly gaining popularity and importance in the more general marketing area. On the practice side, many marketing functions[1] have deployed AI applications, such as robots for consumer greeting, big data analytics for price adjustment and prediction, recommender systems for product and promotional personalization, natural language processing for customer engagement and in-store experience optimization, and sentiment analysis for customer satisfaction tracking, among others.

On the academic side, we similarly observe the proliferation of AI research in marketing. For example, the impact of in-store AI on retailing (Grewal, Roggeveen, and Nordfalt 2017; Grewal et al. 2020), the investigation of the psychological and cultural barriers to consumer adoption of autonomous shopping systems (de Bellis and Venkataramani Johar 2020), the development of explainable automated product recommendation methods (Marchand and Marx 2020), the application of deep convolutional neural networks to forecast retail sales (Ma and Fildes 2021), the use of big data and unstructured data in marketing (e.g. Balducci and Marinova 2018; Grewal, Roggeveen, and Nordfalt 2017; Wedel and Kannan 2016); the applications of various machine learning methods, such as video mining (Li, Shi, and Wang 2019), text analysis (Berger et al. 2019; Humphreys and Wang 2018), topic modeling (Antons and Breidbach 2018), semantic analysis (Liu and Toubia 2018), dynamic online pricing (Misra, Schwartz, and Abernethy 2019); and the impact of AI applications, such as adaptive personalization for music and news (Chung, Rust, and Wedel 2009; Chung, Wedel, and Rust 2016), IoT and consumption experience (Hoffman and Novak 2018; Novak and Hoffman 2019), AI's impact on consumer experiences (Puntoni et al. 2020), on

☆ This research was supported by grants (106-2410-H-002-056-MY3 and 107-2410-H-002-115-MY3) from the Ministry of Science and Technology, Taiwan.
* Corresponding author.
E-mail addresses: huangmh@ntu.edu.tw (M.-H. Huang), rrust@rhsmith.umd.edu (R.T. Rust).

[1] We define the relationship between marketing functions and tasks as that a marketing function comprises multiple tasks, just as consumption activities comprise multiple tasks. This is similar to the relationship between jobs and tasks, with a job comprising numerous tasks. AI augmentation or replacement occurs fundamentally at the task level (Huang and Rust 2018).

https://doi.org/10.1016/j.jretai.2021.03.001
0022-4359/

Please cite this article as: Huang, Ming-Hui, and Rust, Roland T., A Framework for Collaborative Artificial Intelligence in Marketing, *Journal of Retailing*, https://doi.org/10.1016/j.jretai.2021.03.001

service (Huang and Rust 2018), and on the economy (Huang, Rust, and Maksimovic 2019; Rust and Huang 2021), and the strategic use of AI to engage customers (Huang and Rust 2021a).

Although the importance of AI has been well-recognized in marketing practice and research, there are persistent debates about whether AI augments or replaces humans (Huang and Rust 2018; Davenport and Kirby 2015; Frey and Osborne 2017; Malone 2018). Reflected in marketing studies, some studies find support for replacement, such as consumer perceived warmth and liking of anthropomorphized robots (Kim, Schmitt, and Thalmann 2019) and anthropomorphized display of product and consumer's attachment and willingness to pay (Yuan and Dennis 2019), while some studies find support for augmentation, such as the contrasts between frontline employees and AI with respect to dimensions of service training and learning, customer experience, firm strategy, and impact on society (Wirtz et al. 2018) and consumer resistance to using medical AI, with the result of needing human mediation (Longoni, Bonezzi, and Morewedge 2019).

These disagreements generate persistent concerns about the role and impact of AI in marketing, especially regarding to what extent AI should be used to perform marketing tasks in replacement of human marketers, and in what way AI should be used by marketers and consumers for augmentation, to avoid unnecessary replacement. Previous studies have established that there are multiple AI intelligences (Huang and Rust 2018; Huang, Rust, and Maksimovic 2019; Rust and Huang 2021) that can provide multiple benefits in service to engage customers (Huang and Rust 2021a). Huang and Rust (2018) first proposed the novel multiple AI intelligences view, supported by analytical theory, that AI advances from mechanical, to thinking, to feeling intelligence (based on how difficult for AI to mimic human intelligences). Huang, Rust, and Maksimovic (2019) provide empirical evidence based on the U.S. government data for the multiple AI intelligences view and their impacts on the economy, predicting that when AI does the thinking tasks and jobs, humans need to upgrade to feeling tasks and jobs. Huang and Rust (2021a) illustrate how multiple AI intelligences, individually and collectively, can be used to engage customers for different service benefits at different service stages, including standardization, personalization, and relationalization. Huang and Rust (2021b) provide a strategic framework using the multiple benefits of AI for marketing research, marketing segmentation, targeting, and positioning (STP), and marketing actions (4P/4C).

Building on these existing studies, we develop a general framework for collaborative intelligence in marketing to address the important issue of how to use AI to augment marketers and consumers at different intelligence levels. The framework asserts that 1) AI has relative strengths over HI (human intelligences of marketers and consumers) for performing mechanical and analytical marketing and consumption tasks, whereas HI (currently) has relative strengths over AI for performing contextual, intuitive, and feeling tasks, 2) lower-level AI augments higher-level HI, and 3) at a given intelligence level, AI first augments, and then replaces HI. General principles are proposed to guide marketers, consumers, and researchers for collaborative intelligence in marketing.

This paper goes beyond the existing studies in that it lays out the multiple ways and conditions that AI and HI can collaborate, and delineates the collaboration scenarios for both marketers and consumers. Although the application of AI in marketing is gaining popularity in practice, existing studies tend to focus on algorithms for applying AI, the macroeconomic impact of AI (Huang, Rust, and Maksimovic 2019), the replacement effect of AI on human labor (Huang and Rust 2018), the benefits of AI at different stages of service process (Huang and Rust 2021a), or the strategic use of AI for marketing planning (Huang and Rust 2021b); work that guides the collaborative use of AI in marketing is limited.

In summary, this paper contributes to our understanding about the use of AI in marketing by providing a systematic framework for collaborative AI, which leverages the collaborative intelligence of AI, marketers, and consumers, and considers AI's augmentation and replacement of HI from both the marketer's and the consumer's perspectives. We specify conditions for how marketers and consumers can actively leverage AI at different intelligence levels. With this big picture framework, that provides a deeper understanding of collaborative intelligence in marketing, marketing stakeholders can maximize the benefits of AI.

Multiple AI Intelligences

What is AI?

AI is machines that mimic human intelligences computationally and digitally, designed to emulate (or surpass) capabilities inherent in humans, such as doing mechanical, thinking, and feeling tasks. In service research, Huang and Rust (2018) define AI as "machines that exhibit aspects of human intelligence." In computer science, Russell and Norvig (2009) define AI as intelligence demonstrated by computers that mimics human cognitive functions such as problem solving. In consumer research, Longoni, Bonezzi, and Morewedge (2019) define AI as "any machine that uses any kind of algorithm or statistical model to perform perceptual, cognitive, and conversational functions typical of the human mind." Among some of the AI capabilities are robotics to emulate human movement, speech recognition to emulate human listening, computer vision to emulate human vision, natural language processing to emulate human language, and analytics to emulate human thinking.

AI is distinct from other technologies in that it can learn from data and adapt over time autonomously. That is, AI can self-learn (Huang and Rust 2018). This is what distinguishes AI from earlier manufacturing or information technology, such that AI not only can process information for human usage, but also can learn from data and update outcomes without additional programming or human intervention. This characteristic of AI makes collaboration the key variable, because the interaction with HI is two-way, autonomous, and adaptive. It is unlike other technologies that are designed to serve HI in a fixed way, and thus technology acceptance and adoption are central.

Multiple AI Intelligences

These different AI capabilities revealed in the various AI definitions show that there are multiple AI intelligences. This view, first proposed by Huang and Rust (2018), considers that when humans have multiple intelligences (e.g., Gardner 1983), and AI is machines designed to mimic human intelligences, there are potential for developing AI to have multiple intelligences. Their studies show that AI intelligences advance from mechanical, to thinking, and to feeling, ordered by the difficulty with which AI can address them, with mechanical the easiest (for AI) and with feeling the most difficult (Huang and Rust 2018; Huang, Rust, and Maksimovic 2019).[2] In brief, mechanical AI is the lowest level of AI intelligence, learning and adapting only minimally, but being very good at routine and repetitive marketing tasks for standardized output. Thinking AI is data- and analytical-based. It has the ability to process and analyze large amounts of data (i.e., big data) and learn from them for personalized output. Feeling AI should have the ability to recognize, simulate, and react to emotions appropriately, as humans do, but given that AI intelligences are based on data and analytics, current AI does not have true human biological feeling intelligence; instead, it achieves feeling intelligence by analyzing emotional data.

AI advancement tends to be cumulative. Once AI intelligence has advanced to a higher level, it also typically possesses (or could possess) all of the lower-level intelligences. Detailed discussions about the multiple AI intelligences and their benefits are given by Huang and Rust (2018, 2021, and Rust and Huang (2021).

Collaborative Intelligence in Marketing

The view that AI can have multiple intelligences gives rise to multiple complementary ways of implementing collaborative AI. We use the term human intelligence (HI) to refer to both marketer and consumer intelligences. Both marketers and consumers can use AI varying in intelligence levels for marketing and consumption tasks. In the paper, when we speak of marketing, we include both the marketer and the consumer.

We develop three general principles and elaborate their sub-principles about how collaborative intelligence can be achieved in marketing at different intelligence levels, for marketers and consumers, respectively. The framework first identifies the relative strengths of AI and HI at each intelligence level, based on realizing that AI is computational whereas HI is biological. The framework then specifies how these relative strengths can complement each other for collaborative intelligences at each intelligence level. Finally, the framework uncovers the mechanism for when the collaboration will need to be advanced to a higher intelligence level.

Specifically, general principle 1 (GP1) posits that AI and HI each can perform marketing tasks for which they have relative strengths at different intelligence levels. Taking the computing nature of AI and the biological nature of HI into consideration, current AI has the relative strengths of mechanical and analytical intelligences, whereas HI has the relative strengths of contextual, intuitive, and feeling intelligences.

General principle 2 (GP2) posits that based on GP1, lower-level AI should be used to augment higher-level HI. Three sub-principles (GP2a–2c) are laid out to specify how marketers and consumers can use different AI intelligences to complement their marketing and consumption tasks. Mainly, mechanical AI can augment contextual HI for undesirable marketing tasks (GP2a), mechanical and analytical AI can augment intuitive HI for smarter marketing decisions (GP2b), and all AI intelligences can augment feeling HI for better emotional intelligence in marketing.

General principle 3 (GP3) posits that within each intelligence level, AI first augments and then replaces HI, based on a historical observation and projection into the future of AI continuing advancement from mechanical, to thinking, to feeling, that will push the collaboration to a higher intelligence level when AI can perform all lower-level intelligence tasks autonomously (i.e., automation).

Overall, the set of general principles constitutes a general framework for a dynamic picture of collaborative intelligence in marketing that determines at each intelligence level how AI and HI can collaborate, based on their respective relative strengths, and when this collaboration should be advanced to a higher intelligence level.

In the following sections, we first develop the three general principles, and then discuss implications of these general principles for marketers, consumers, and researchers, respectively. Table 1 summarizes the general principles for collaborative intelligence in marketing and implications for various stakeholders.

GP1: AI-HI Relative Strength

In this general principle, we lay out the relativee strengths of AI and HI, which sets the theoretical foundation for collaborative intelligence. Given that machines are computational, whereas humans are biological in nature, AI and HI each has its relative strengths on the three intelligences. Specifically, machines' relative strengths currently hinge on data, computation, and analytics. Thus, its mechanical intelligence is typically non-contextual due to context often lost when data are extracted (e.g., text mining stems key words from online customer reviews), its thinking intelligence is analytical with big data as the input and with algorithms and models as the way to learn (e.g., provide recommendations based on like-minded customer data and personalization algorithms), and its feeling intelligence is analytical too, but with emotional data as the input (e.g., analyze a driver's emotional states using machine learning based affective analytics).

[2] Huang and Rust (2018) consider four AI intelligences: mechanical, analytical, intuitive, and empathetic, and Huang, Rust, and Maksimovic (2019) combine analytical and intuitive into "thinking" AI. We follow the three-level framework but also refer to the two sub-types of thinking AI whenever necessary. The distinction between analytical and intuitive intelligence is sometimes important, because analytical intelligence is "easier" for AI than intuitive intelligence, which requires what researchers call general intelligence or "general AI" (Kurzweil 2005).

Table 1
Summary of general principles for collaborative intelligence in marketing and implications for various stakeholders.

General principles	Marketers	Consumers	Researchers
GP1 (AI-HI relative strength). Current AI has strengths on mechanical and analytical intelligences, whereas HI has strengths on contextual, intuitive, and feeling intelligences	Optimize collaborative intelligence, conditioning on AI-HI complementarity, considering nature of tasks and level of intelligences	Understand the consumption opportunities and constraints due to the AI-HI complementarity	• Investigate empirically the comparative strengths of AI and HI and the best mix of AI and HI at the macro, meso, and micro levels • Examine empirically consumer reactions to the opportunities and constraints resulting from AI-HI complementarity • Explore innovative ways that the intelligence multiplicity can be used for collaborative intelligence
GP2 (AI-HI collaboration). Lower-level AI intelligences augment higher-level HI intelligences	Manage collaborative intelligence based on GP2a-2c	Assist consumption using the right AI based on GP2a-2c	• Obtain AI marketing task and job data and investigate the nature of the tasks and jobs to optimize the AI-HI joint workforce • Manage the AI-HI team to improve marketing and consumption value
GP2a. Mechanical AI augments contextual HI for undesirable marketing tasks	Use mechanical AI for human undesirable marketing tasks	Use AI for saving time and effort on mechanical consumption tasks	• Explore how contextual data can be better captured • Address the boundary conditions under which mechanical AI can be contextual • Examine task undesirability as the basis of collaboration • Explore qualitatively AI-HI interaction in context
GP2b. Mechanical AI and analytical AI augment intuitive HI for smarter marketing decisions	Leverage data and analytics for marketing innovation	Augment consumption intuition, judgment, decision	• Explore the approaches to and boundary conditions for data- and analytical-support marketing innovation and creativity • Investigate the ways to alleviate unexplainable, biased, or context-unaware AI applications in marketing • Examine the ways consumption intuition can be enhanced to increase consumer utility and well-being
GP2c. All AI intelligences augment feeling HI for better emotional intelligence in marketing	Recognize the value of human feeling intelligence	Augment consumption experiences and emotions	• Examine empirically the ability of AI for emotional outcomes (engagement, satisfaction, and experience, etc.) • Explore approaches to capturing emotional data and modelling feeling AI • Scenario experiments for understanding future collaboration for feelings • Personalization incorporating emotions • Explore sustainable AI for augmenting human value
GP3 (AI-HI augmentation-replacement duality). AI first augments and then replaces HI at each intelligence level	Enhance collaborative intelligence over time, conditioning on the intelligence and cost gaps between AI and HI	Understand this duality for delegating consumption tasks	• Investigate empirically HI readiness for AI automation • Use panel or time series analysis to understand the antecedents and sequences of marketing tasks performed by AI or HI over time • Measure empirically the gaps across intelligence levels, marketing conditions, and consumers

By contrast, humans' current relative strengths hinge on their contextual, biological, cultural roots for the three intelligences. Humans' mechanical intelligence is contextual, with humans acting and reacting in the context where marketing takes place (e.g., service provision), humans' thinking intelligence can be intuitive, with heuristics being applied for decisions (e.g., developing marketing strategies or being risk aversive in financial decisions), and humans' feeling intelligence is biological and cultural, having the capability to "experience" emotions biologically and react to emotions appropriately, given cultural norms (e.g., being empathic in frontline interactions).

In Fig. 1, we put the characteristics of AI's and HI's intelligences in brackets to highlight the basis of their respective intelligence. In the following discussion of the relative strengths of current AI versus HI, the description in brackets about their unique intelligences is omitted for simplicity.

GP1. Current AI Has Strengths on Mechanical and Analytical Intelligences, whereas HI Has Strengths on Contextual, Intuitive, and Feeling Intelligences

AI's strengths

AI has relative strengths on mechanical and analytical intelligences. AI's mechanical intelligence already outperforms HI for many routine and repetitive marketing tasks. Mechanical AI often manifests as embodied robotics; machines that are programmed to do a given task in a controlled environment (Cockburn, Henderson, and Stern 2018), sometimes (but usually

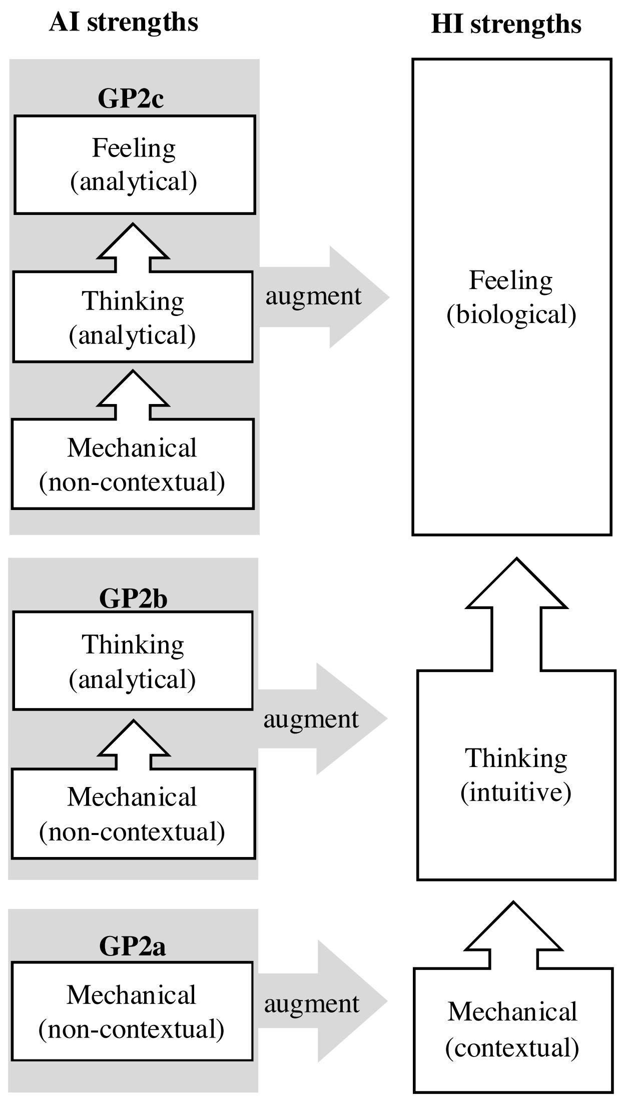


Fig. 1. Collaborative AI: lower-level AI augments higher-level HI.

not) with a humanoid physical appearance. For example, Rethink Robotics' industrial robot Baxter automates highly specialized industrial processes and iRobot's Roomba vacuum senses and interacts within a house. In marketing, various forms of mechanical AI have been used; for example, collaborative robots (cobots) help with packaging, drones distribute physical goods, self-service robots deliver service, and service robots automate social presence in the frontline (Mende et al. 2019; van Doorn et al. 2017). All these applications perform marketing tasks that are routine and repetitive and do not require context.

AI's analytical capability has been used widely to perform marketing tasks, most often using neural network-based machine learning to "think." It is "narrow AI" that is designed to perform a narrowly defined task very well, such as playing chess or Go. In this kind of learning, machines do not need to have knowledge to answer questions, but simply with big data, great computing power, and the right algorithms and models, they can be very powerful in generating output that is seemingly intelligent. For example, AlphaGo plays the game of Go by learning from countless past games, and comes up with the strategies that have the highest chance to win. It does not know *why* these strategies would win in a certain situation. This is the level of AI that has received wide research attention in marketing, such as big data and marketing analytics (Chintagunta, Hanssens, and Hauser 2016; Liu, Vir Singh, and Srinivasan 2016; Wedel and Kannan 2016), adaptive personalization systems (Chung, Rust, and Wedel 2009; Chung, Wedel, and Rust 2016; Dzyabura and Hauser 2019; Liebman, Saar-Tsechansky, and Stone 2019), automated product recommendations that have the ability to provide explanations (Marchand and Marx 2020), deep learning for personalized point-of-interest recommendation (Guo et al. 2018), and video-based automated recommender systems (Lu, Xiao, and Ding 2016). All these applications leverage the analytical capability of AI.

AI's analytical capability has also been applied to perform many feeling tasks, creating the impression that AI has feeling intelligence like humans. This AI capability has been used to analyze emotional data, which can be in text (e.g., sentiment in online reviews), audio (e.g., tone in call center conversations), visual (e.g., facial expressions in reaction to TV commercials), or physiological signals (e.g., heartrate and blood pressure sensed by smart wearables).

Analyzing emotions in text-based online reviews and social media content is common in the marketing literature (Hartmann et al. 2019; Hewett et al. 2016; Ordenes et al. 2017; Rust et al. 2020; Tirunillai and Tellis 2012). For example, the valence of consumer generated content is found to relate to the stock market performance of the firm (Tirunillai and Tellis 2012). The sentiment expressed by consumers in social media, including explicit and implicit language and discourse patterns, is analyzed to understand consumer responses using their own language (Hewett et al. 2016; Ordenes et al. 2017). Brands can track their reputation through text and sentiment analyses tweets, reviews, and social media posts (Rust et al. 2020).

Emotional voice analytics are used extensively in call centers. Shim et al. (2016) discuss many real-world cases that deploy phonetic analytics to call centers to recognize and analyze phone conversations and interactions that help respond to customer complaints and predict future purchases. Luo et al. (2019) demonstrate the use of voice simulation and analytics to do call-out marketing.

Sensing and analyzing facial expressions are in wide commercial use. Major auto insurance companies use in-car sensors to detect a driver's emotional state to determine the premium. Haptics are used by marketers to sense consumer physiological signals for immersive marketing experiences. Coca-Cola uses emotion-recognition software to adjust ads based on consumer emotional response. Li, Shi, and Wang (2019) demonstrate that video content, such as TV and online video advertising, user-generated videos, product videos, movies, and video games, can be mined for various marketing purposes.

HI's strengths

HI currently has relative strengths on tasks that require context, intuition, and feeling. Human mechanical intelligence is contextual, involving eye-hand-foot coordination, finger and manual dexterities, face-to-face contact, and physical presence in a place (Autor and Dorn 2013; Frey and Osborne 2017) that are difficult for machines to perform alone. The distinction between service tasks and manufacturing tasks captures this nuance: service provision involves contextual co-production, whereas physical goods production does not (meaning that production and consumption are separable). This difference results in a much lower degree of service automation than manufacturing automation because humans can (currently) provide contextual service better than machines. Thus, we see that for service provision, there are cobots that work together with humans with cobots performing non-contextual mechanical marketing tasks (e.g., sorting products for shipping) and with humans performing contextual mechanical marketing tasks (e.g., checking randomly for accuracy).

Human intuition is currently a uniquely human strength (although that will likely not always be the case). Intuition is the ability to do commonsense reasoning beyond humans' explicit understanding (i.e., Polanyi's paradox, Autor 2014), or to apply knowledge to new situations. Humans acquire or accumulate intuition or common sense from their surroundings and interactions. Intuition is the ability to acquire knowledge without analytical reasoning (Cholle 2011; "Intuition," Merriam-Webster 2019), whereas common sense is knowledge that most people know without reflection or argument (van Holthoorn and Olson 1987; "Commonsense," 2010). Intuition (or common sense) is real-world knowledge, acquired and accumulated throughout a human's entire life experience; it is not learned from formal education (Davis and Marcus 2015). Based on evolutionary psychology, Wright (2002) considers market-related intuition (i.e., marketplace metacognition in his study) as consumers' everyday knowledge about the marketplace, developed over their life span.

Intuition, in contrast to deliberate, rational thinking (e.g., Hall, Ahearne, and Sujan 2015), is considered to be a decision shortcut (heuristic) in consumer research. For example, bounded rationality incorporates risk aversion into decision-making (Kahneman and Tversky 1979) and the Elaboration Likelihood Model (ELM) includes the peripheral route of persuasion in consumers' responses to advertisements (Petty and Cacioppo 1986). Because human intuition is often not easily explainable, it is difficult for machines to emulate. Thus, we see the call for "general AI" (i.e., AI is designed to emulate a wide range of human cognition, Kurzweil 2005), as this level of intelligence is considered by many computer scientists to be the bottleneck of AI development.

Creativity and innovation are manifestations of intuition. Humans typically produce music and art following instinct and inspiration, not by analyzing data. Thus, whether innovation should be customer-lead (i.e., based on customer data) has become a debate in marketing. Caring too much about what customers currently want may result in a loss of innovativeness (Voss and Voss 2000).

Human feeling intelligence is biological and cultural. Human emotions have a biological component that machines do not have, and the appropriateness of emotional reactions is contextually, socially, and culturally dependent; both constitute biological and cultural barriers to machines. An appropriate reaction in one context or culture may not be appropriate in another context or culture.

Emotions are biological. Biological intelligences are demonstrated by humans and animals and are associated with physiological reactions to external stimuli to adapt to the environment. Neuroscience is one such discipline that studies the structure and function of the nervous system that is unique to biological beings ("Neuroscience" 2019). Some famous psychological principles have been experimentally established by animal psychologists, such as Pavlov's (1960) classical conditioning learning and Skinner's (1938) operant conditioning learning. In consumer behavior, Hasford, Kidwell, and Hardesty (2018) find that psychological conditioning can be applied to the experience of emotion and the subsequent attitudes toward a conditioned stimulus (i.e., different beer brands in their study).

Emotional experience is contextual. Emotional intelligence exists in context. Kidwell et al. (2020) find that consumers feel more satisfied with their service interactions when the service employees' emotional ability is similar with theirs. Gabbott, Tsarenko, and Mok (2011) find that customers' emotional intelligence, i.e., the ability to deal with own and other's emotions, shapes their responses to service failure and service recovery efforts. These service studies show that emotions are experienced during interactions.

Emotional intelligence is the capability to recognize, experience, and react appropriately to self and others' emotions (Goleman 1996). This definition reveals that emotional reaction is social/cultural. Appropriate emotional reactions are determined by social/cultural norms. Wright (2002) uses the term social intelligence and considers that these reactions are learned over a consumer's life span by virtue of functionally specialized evolutionary processes. "Functional" in this context means that an appropriate reaction increases the odds of survival whereas an inappropriate reaction decreases the odds. Thus, over time, consumers learn what emotional reactions are appropriate that increase their fit to the society. Gill (2020) finds that harm to a pedestrian is considered to be more permissible by an autonomous vehicle than by a human driver in a regular car, a finding implying that what is right and what is wrong can also be shaped by the advancement of AI in a society.

Summary

The relative strengths of AI are mechanical and analytical intelligences, and the relative strengths of HI are contextual, intuitive, and feeling intelligences, which suggests to marketers how to optimize collaborative intelligence and to consumers the need to understand human strengths in consumption.

For marketers, the common misuse of AI is to prematurely use some AI intelligence when it is a human's strength, such as letting AI be fully in charge of product design (which requires creativity) or price negotiation (which requires intuition and feeling intelligences), when humans can do those intuitive tasks better. When marketers use the wrong or immature AI, it often backfires. Mende et al. (2019) find that humanoid robots generate consumer discomfort that changes consumption decisions.

Humanoid robots are used to augment consumption experiences and emotions in this case, but consumers are not ready, because the robots are not mature either. Thus, embedded AI or non-humanoid AI may be more appropriate in this situation.

For consumers, if they have a better understanding of these relative strengths, they can leverage the opportunities and constraints enabled by AI (e.g., Hoffman and Novak 2018; Novak and Hoffman 2019), and can make more informed consumption decisions about accepting or rejecting AI applications. Studies find that many consumers tend to reject AI due to lack of understanding. For example, Longoni, Bonezzi, and Morewedge (2019) find consumer resistance to personal medical AI, and that such resistance can be alleviated if such AI is used to support, rather than replace, the human healthcare provider. Luo et al. (2019) find that consumers hang up on an AI chatbot once they know they are talking to a bot. We discuss further implications from this general principle in Discussion section.

GP2: AI-HI Collaboration

The relative strengths of AI and HI set the foundation for AI-HI collaboration. We start from the general principle that lower-level AI intelligences augment higher-level HI intelligences (GP2), and then elaborate GP2 into the set of sub-principles of GP2a to GP2c to specify the conditions for collaboration. Fig. 1 illustrates the general principle that lower-level AI augments higher-level marketer and consumer intelligences.

GP2. Lower-Level AI Intelligences Augment Higher-Level HI Intelligences

We posit that lower-level AI intelligences augment higher-level HI intelligences, but not the other way around, because when AI outsmarts or is equally smart as HI in a given intelligence level,[3] it can perform the marketing function autonomously, and thus is more likely to replace HI. We discuss this AI-HI relationship more in general principle 3 (GP3). Given current AI's relative strengths with respect to mechanical and analytical intelligences, and HI's relative strengths with respect to contextual, intuitive, and feeling intelligences, GP2a to GP2c discuss how lower-level AI can be used to augment higher-level HI to avoid unnecessary or counter-productive HI replacement and optimize marketing performance.

GP2a. Mechanical AI Augments Contextual HI for Undesirable Tasks

Given that AI's mechanical intelligence can do a better job with non-contextual tasks (e.g., sensing, tracking, recording, and retrieving data), whereas HI's mechanical intelligence is more capable of handling contextual tasks (e.g., frontline service interactions), collaboration at the mechanical level is most common for marketing tasks that are somewhat contextual but are undesirable for humans to do (AI can do non-contextual tasks on its own). Contextual tasks require the presence of HI, while undesirable tasks constitute a boundary condition for assigning the tasks to AI. Task undesirability can be due to machines being able to do better (e.g., for consistent and standard output) or humans being less willing to do (e.g., for repetitive, routine, or dangerous tasks). For example, various self-check-in or check-out systems in retailing, such as grocery stores, restaurants, and hotels, free employees from the repetitive, boring tasks. Chinese hotpot chain restaurants, HaiDiLao, use mechanical arms to prepare and handle hot soup base in the kitchen (i.e., the task is dangerous), social robots Pepper to deliver food to the table-side (i.e., the task is routine and repetitive), and human waiters to serve the food to the table and interact with customers (i.e., the task is contextual).

Likewise, consumers can use various mechanical AI to do the tasks that they are unwilling to do. For example, consumers can use Roomba to do house cleaning, which is an undesirable task but is contextual in the consumers' residences; use smart home applications to switch on/off light or appliances remotely, which is an unable-to-do task when consumers are away from home; or ask Alexa for weather information without needing to type in questions to any search engine for answers, which is a task for which mechanical AI can save consumers' time and effort.

GP2b. Mechanical AI and Analytical AI Augment Intuitive HI for Smarter Marketing Decisions

Both mechanical AI and analytical AI, the two levels of AI intelligences that are lower than human intuitive thinking intelligence, can augment intuitive HI. Given that AI intelligences are cumulative, the two scenarios discussed below should be viewed as whether a collaborative scenario relies more on mechanical AI or analytical AI, but not either-or.

Mechanical AI augments intuitive HI

This type of collaboration is most suitable for manual and process-driven marketing, such as automating the execution of email marketing, search campaigns, researching keywords, or changing social media targets (Sutton 2018). In marketing, email marketing is the most common marketing function that is automated. Liedke (2020) lists the seven best marketing automation applications (defined as automating marketing tasks for a business), and all of them concentrate on email marketing, such as automating email list collection, email sending, and email tracking, with some including social media marketing, such as landing page automation. Human marketers thus only need to formulate email marketing strategies for email marketing AI to implement.

Intuition plays an important role in many consumption decisions. Mende et al. (2019) demonstrate that interacting with mechanical service robots in a restaurant changes consumers' intuitive thinking about what to eat and how much to eat (Mende et al. 2019). For consumers, mechanical AI can augment intuitive consumption by taking care of repetitive and routine tasks while leaving the intuitive tasks to consumers. For example, smart refrigerators can update and refill groceries automatically, and

[3] AI can also replace HI when it is almost as smart as HI, but is cheaper (Rust and Huang 2014).

consumers can concentrate on what food to prepare and what food to shop for for an upcoming party (which are often spur of the moment).

Analytical AI augments intuitive HI

This is a very common type of collaboration due to the popularity of big data and analytics. Malone (2018) describes this type of collaboration as narrow AI (good at specialized intelligence) tackling parts of the problem at hand, and general HI (good at general intelligence) doing the rest (i.e., decision support in modern language). Kleinberg et al. (2018) show that machine learning predictions can help human judges' bail decisions by providing payoff functions and decision counterfactuals. Jarrahi (2018) argues that the analytical capability of AI is especially useful for human decisions and judgments when uncertainty and subjectivity are involved.

In marketing, it is also commonly observed that higher-level managers use marketing analytics for strategic decisions, R&D, and creativity. For example, marketers' creativity can be enhanced. The fashion clothing company Gap uses predictive analytics for fashion trends, assisting human designers to design clothing that better matches customer preferences. Google uses big data and analytics to keep its leadership in innovation, while avoiding relying too much on data (e.g., data mining) that threaten to make a marketer less innovative (i.e., less future oriented). The company achieves this by data-support, not just data-only innovation, because the latter can only achieve incremental improvement in performance (Mohr 2020). In this collaborative scenario, human creativity (i.e., innovation, R&D) can be powered by data analytics. Fügener et al. (2020) find that using AI to complement humans for intuitive tasks enables humans to exceed human and AI performance levels; by simply following AI's suggestions, human lose their complementarity advantages. The results imply the need to have analytical AI augment intuitive HI, rather than relying on analytical AI too much.

For consumers, analytical AI can be used to make complex consumption decisions, such as buying a house or a car, or similarly be used to facilitate creativity, such as composing music. Tailor Brand's Logo Maker visualizes logo design to help consumers self-design logo. Those are examples of using AI to enhance creativity that can be applied by consumers to make smarter decisions or generate more creative outputs.

GP2c. All AI Intelligences Augment Feeling HI for Better Emotional Intelligence in Marketing

All levels of AI intelligence can be used to augment HI for better emotional intelligence, but human feelings are fundamentally irreplaceable (at least until biological computing is more advanced). Huang, Rust, and Maksimovic (2019) and Rust and Huang (2021) point out that managing feeling is critical in the thinking AI age (the "Feeling Economy").

Mechanical AI augments feeling HI

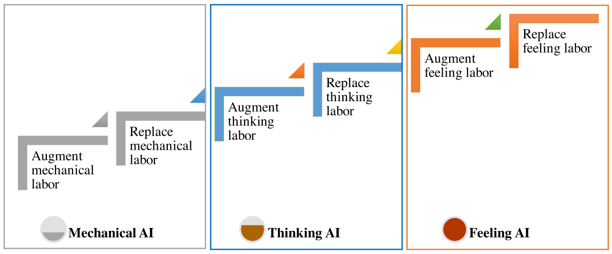
Various types of mechanical AI have been used and studied in marketing to capture emotional data and augment interactions and experience. Marketers use smart wearable devices like Fitbit to capture consumers' biological signals for understanding their emotions and experience. Apple's smart earbuds, AirPods, is patented to equip with biometric sensors that can record consumers' heart rate, temperature, and movement. When connecting with Siri, its audio quality and customized fit create an immersive usage experience (Golembiewski 2019). Service robots in a restaurant, humanoid or not, have been used to perform simple, repetitive interactions with consumers that augment their feelings, positively or negatively (Mende et al. 2019). Recent research has begun to explore the impact of haptic marketing that use haptics technology to capture multimodal emotional data and create a multisensory online experience for consumers (Petit, Velasco, and Spence 2019).

Analytical AI augments feeling HI

Many marketing tasks are high touch in nature, and thus consumer emotions are the key process or outcome variables. Analytical AI can analyze cognitive data (online reviews, social media posts, call center conversations) and emotional data (sentiment in reviews and posts, voice tone in phone calls, and facial expressions in interactions and conversations) in those tasks (e.g., interaction and experience) and provide analytically-based results or recommendations for human marketers and customers to act upon.

When analytical AI is used to analyze cognitive data, it augments feeling HI in a thinking way. For example, Netflix's movie recommender personalizes movie lists for consumers, augmenting the marketer's capability to increase the relevancy of the recommendation, as well as the consumer's satisfaction with Netflix and enjoyment with the recommended movies (Johnston 2019). In retailing, Alibaba's Fashion AI system analyzes customer preferences based on what they bring into the fitting room, and then uses smart mirrors to display each customer's selected items and suggest complementary items, enhancing retailers' relationships with customers by providing a great fitting room experience.

When analytical AI is used to analyze emotional data, it augments feeling HI in a feeling way. For example, Cogito's voice analytics help call center agents identify customer moods and provide guidance for agents to handle customer dissatisfaction more emotionally intelligently. IBM's Watson Tone Analyzer, a sentiment analysis tool, enables chatbots to detect customer tones so that dialog strategies can be adjusted to the conversation, resulting in more satisfied customer service. Affectiva provides analytical feeling AI service to various fields, such as detecting whether a driver is falling asleep while driving and issuing an alert that promotes safe driving, and helping advertisers to measure consumer emotional response to digital content, among others and adjust content accordingly to shade consumer attitudes more favorably. Facebook augments consumers' social networking experience by providing analytical results of the sentiment in conversation (happy or unhappy, annoyed already, or bored by the conversation, etc.), from which consumers can better understand their friends' moods during interactions, and react accordingly.



Implications for marketers illustrated					
Assembly lines help workers assemble parts together	Smart human-less factory	In-car smart systems assist human drivers	Driverless cars	Voice analytics augment customer service agents	Natural language processing systems replace human customer service agents
Implications for consumers illustrated					
Electronic upright vacuums help consumers do house cleaning chores	Robotic vacuums replace consumer labor for house cleaning	Price or product comparison websites help consumers choose the right product at the price	Product recommendation engines replace consumer efforts in finding the right product	Sentiment analysis for online reviews helps consumers decide which brand to buy	Facial expression recognition systems recommend products for consumption based on consumer moods

Fig. 2. AI first augments and then replaces HI at each intelligence level.

GP3: AI-HI Augmentation-Replacement Duality

GP3. AI First Augments and Then Replaces HI at Each Intelligence Level

Machine–human relationships may involve augmentation or replacement of human labor. Augmentation means that AI complements HI for a marketing function based on their respective relative strengths (GP1 and GP2), whereas replacement means that AI can perform all tasks of a marketing function without human labor (i.e., marketing function automation). Any marketing function is made up of tasks, and each individual task typically focuses on one intelligence level (Huang, Rust, and Maksimovic 2019). For example, the function of digital marketing involves tasks such as posting and bidding for ad space, personalizing ad content, and emotion sensing from posted messages. The function of pricing involves tasks of payment, price setting, and price negotiation.

We posit that within each level of intelligence, with continuing maturation of AI, AI first augments HI (i.e., when AI assumes some tasks of a marketing function), and then replaces HI (i.e., when AI assumes all tasks of a marketing function). Fig. 2 illustrates this general principle. Thus, according to GP3, the AI-HI relationship is not a simple scenario of either augmentation or replacement, as the existing literature suggests; instead, marketers need to take into consideration the level of AI intelligence and the level of intelligence required by marketing tasks that make up a marketing function.

The existing literature has tried to resolve whether AI augments or replaces HI issue. Using the term automation-augmentation paradox to describe the issue, Raisch and Krakowski (2020) define augmentation as "humans collaborate closely with machines to perform a task" and automation as "machines take over a human task." They take a single thinking intelligence view (they define AI as "machines performing cognitive functions usually associated with human minds, such as learning, interacting, and problem solving (Nilsson, 1971)") to disentangle the paradox, and refer to both temporal and spatial scales to account for the so-called paradoxical relationship. The temporal scale considers that there is a cyclical relationship between automation and augmentation over time, and the spatial scale considers that there is interdependence between various tasks; both create the tension between automation and augmentation.

General principle 3 provides a parsimonious account of the AI-HI relationship. The idea that there are multiple intelligence levels capture the spatial scale, and the idea that machines first augment and then replace humans at each intelligence level captures the temporal scale. Here we take a historical view and project into the future to show that machines first augment and then replace humans *within a given intelligence level*.

Machines are developed and designed with the intention to augment humans (e.g., be more productive or more effective in doing given tasks). However, history shows that as machines outsmart humans in a given intelligence level, they eventually become autonomous, doing the tasks without human help.

In the 19th century industrial revolution, we saw that manufacturing technologies, such as assembly lines, augmented unskilled mechanical workers to assemble parts together, greatly enhancing production efficiency. With the continuing advancement of such mass production systems to become mechanical AI, machines can often automate those repetitive mechanical tasks and replace unskilled mechanical workers totally. We thus see widespread machine-only production, such as smart human-less factories.

In the "hard service" (i.e., thinking) economy, we see that thinking AI, such as in-car smart systems, collects driving data and provides analytics that augment car technicians' diagnosis of car problems and augment human drivers' safe driving. Now we see that driverless cars are becoming available that can replace human drivers altogether in the foreseeable future.

In the "soft service" (i.e., feeling) economy, we see that feeling AI, such as voice analytics, conducts real-time analysis about call center agents' conversations with customers, and provides suggestions about the best way to respond. With the advancement of natural language processing, that not only can recognize customer emotions but also can simulate the human voice to respond to customer emotions, some companies have used such systems to call out to potential customers, replacing human agents (Luo et al. 2019). Huang, Rust, and Maksimovic (2019) provide a detailed account of this migration of the economy from physical, to thinking, to feeling, due to the three AI intelligences. Rust and Huang (2021) provide a comprehensive view about this economy transition with different generations of technology as the driving force.

This brief historical sketch shows that machine-human relationships can involve augmentation and/or replacement: when a new generation technology is invented (i.e., disruptive technology), it tends to augment humans, but as the technology matures (i.e., becomes mainstream technology), it can often outsmart humans at that level of intelligence, and can perform all tasks of a marketing function at that intelligence level autonomously. When that happens, the machine-human relationship turns to replacement of HI by AI.

This general principle provides a mechanism about why a given level of AI intelligence augments or replaces HI, and the timing that marketers need to advance their collaborative use of AI to a higher level. Thus, the various collaborative scenarios discussed in GP2 is not static; rather, it is dynamic over time. When marketing tasks at a lower intelligence level can all be done by AI, marketers need to move up to a higher intelligence level for AI-HI collaboration.

Discussion

The set of general principles, both from the marketer and the consumer perspectives, provides the following implications for marketers, consumers, and researchers for collaborative intelligence in marketing at varying degrees of AI intelligence, which is dynamic over time. Table 1 summarizes these general principles and implications for various stakeholders.

Implications for Marketers

Optimizing, managing, and enhancing collaborative intelligence based on the three sets of general principles imply that using AI for marketing functions should be strategic: it should not be data- or technology-led, that is, it may not work to use whatever AI is available in the market when the marketer or the consumer may not be ready, or use whatever AI that works based on trial-and-error results that may waste valuable data, technology and human resources of the marketer. These general principles provide some directions for marketers to follow for teaming AI and HI.

Optimize collaborative intelligence

GP1 identifies that current AI has relative strengths on mechanical and analytical intelligences, whereas HI has relative strengths on contextual, intuitive, and feeling intelligences. To optimize collaborative intelligence, marketers need to maximize AI-HI complementarity based on their respective strengths.

Any marketing function typically involves tasks requiring difference intelligences. In general, the more mechanical and analytical tasks in a marketing function, such as service delivery (Huang and Rust 2021a; Mende et al. 2019) or personalized recommendation (e.g., Chung, Rust, and Wedel 2009; Chung, Wedel, and Rust 2016), the more AI can be used.

Alternatively, the more contextual, intuitive, and empathetic tasks in a marketing function, such as service interaction (Huang and Rust 2021a; Kidwell et al. 2020), marketing strategy development (Huang and Rust 2021b), or personal health service (Longoni, Bonezzi, and Morewedge 2019), the more HI should be used. Specifically:

At the mechanical level, AI can automate non-contextual tasks while supporting HI for contextual tasks. For example, some restaurants use smart devices to let customers place orders themselves. While this approach is good for fast food restaurants, which focus mostly on operational efficiency, it may not be ideal for high-end restaurants, where contextual interaction and personal service are an integrated part of the dining experience. Also, as discussed when developing GP2a, for tasks that are undesirable or difficult for human employees to do, mechanical AI can help.

At the thinking level, AI can automate data analytics while supporting HI's intuition (e.g., creativity). For example, AI can be used for segmentation (segment recognition), targeting (segment recommendation), and positioning (segment resonance) (Huang and Rust 2021b). Nevertheless, sometimes marketers use it the other way round, by relying too much on analytics and undermining the importance of human intuition. For example, Lexus car's 2018 "Driven by Intuition" commercial used machine learning to produce the script of the ad by learning from 15 years of luxury ads. The ad is eye-catching and feeling-rich, but the consumer segmentation and value proposition of the car appear to be vague, indicating that the role of human intuition in creating an effective ad may be undervalued.

At the feeling level, AI can automate affective analytics while supporting marketers for interaction and communication with customers. As the discussion of the AI-HI relative strengths revealed, feeling intelligence is not the strength of AI yet, but we often see that marketers are too eager to use AI for feeling tasks, such as having chatbots doing call-out marketing to persuade customers to renew their financial plans, resulting in customer discomfort when customers realize they are talking to a bot (e.g., Luo et al. 2019). This shows that, similar to the immature use of analytical AI for intuition, marketers should recognize the value of human feeling intelligence, and use all levels of AI intelligences to augment it.

Manage collaborative intelligence

The set of GP2 principles provides specific guidelines about how to manage collaborative intelligence in marketing, within a given intelligence level and across different intelligence levels.

In general, mechanical AI can be used to augment contextual HI for undesirable tasks such as using mechanical arms in the kitchen for food preparation or using Roomba for house cleaning. Moving one intelligence level higher, mechanical AI such as service robots can augment intuitive restaurant food consumption (Mende et al. 2019), and analytical AI can complement humans for smarter decisions (Fügener et al. 2020), especially when there are uncertainty and subjectivity involved (Jarrahi 2018). Moving one intelligence level further higher, all levels of AI intelligences can augment human feeling intelligence, such as smart headsets creating immersive music experience (Golembiewski 2019), movie analytics personalizing entertainment (Johnston 2019), and social emotional analytics facilitating social interactions on Facebook. Specifically:

At the mechanical level, use AI for human undesirable marketing tasks. GP2a has implications for service marketing such as retailing, given that handling physical goods is the strength of mechanical AI. Not all mechanical marketing tasks are equal; some are more contextual and more difficult for mechanical AI to do. Those are mostly service tasks, due to the co-production nature. This creates a scenario in which even for mechanical service tasks, as long as they are non-contextual, mechanical AI can apply; most likely for machines to do more dangerous or undesirable tasks or tasks that humans cannot do as well.

At the thinking level, leverage data and analytics for marketing innovation. GP2b has direct implications for artificial innovation and creativity. Innovation can be powered by data and analytics, such as is the case in the noticeably short product lifecycle in the fast fashion industry, that relies on predictive analytics for design new clothing and accessories. Marketers' intuitive capability, such as developing new market positioning, can be powered by data analytics.

At the feeling level, recognize the value of human feeling intelligence. GP2c implies the superiority of human feeling intelligence. Various areas of marketing require feeling intelligence, but marketers sometimes tend to emphasize thinking intelligence (e.g., analytics) over feeling intelligence (e.g., being empathetic with customers). This general principle highlights the need to identify those marketing tasks that are emotionally rich, and have feeling-intelligent employees handle those tasks, with the assistance of AI at various intelligence levels.

Enhance collaborative intelligence over time

GP3 lays out the general principle that "AI first augments and then replaces HI" at a given intelligence level, implying to marketers that not only do they need to optimize collaborative intelligence, but they also need to consider when it is the right time for AI to fully automate a marketing function (Huang and Rust 2021a). The historical account that AI advances from mechanical, to thinking, to feeling, giving rise to different economies, illustrates this evolving machine-human relationship (Rust and Huang 2021). Two factors can be considered when applying this general principle to marketing:

The intelligence gap between AI and HI can be used as a proxy for AI readiness for marketing automation at a given intelligence level. The smaller the gap between AI and HI, the more ready the AI is for automating marketing tasks at that level. The Turing test can serve as a practical test for this gap. If an AI application can pass the Turing test so that a consumer cannot tell whether it is a machine or human performing the task, or a consumer can tell but doesn't mind the small difference (i.e., the gap is tolerable), AI can safely be used to replace HI for that task. If all tasks of that marketing function pass the Turing test, the marketing function can be totally automated by AI.

Another consideration is whether AI or HI is more cost efficient for performing a marketing task. Some AI, for example embodied Pepper robots, are costly to deploy, whereas some AI, for example embedded conversational bots, can be more cost efficient than human agents. Thus, when the cost gap between AI and HI is smaller, such as when AI is cheaper but almost as smart as HI, it is enticing to use more AI for automation and less HI (Rust and Huang 2014).

In both cases, when the intelligence and cost gaps between AI and HI are small and AI can perform more cost-efficiently than HI for most tasks of a marketing function at a given intelligence level, humans marketers need to upskill to start the augmentation-replacement duality at a higher intelligence level. For example, frontline customer service agents need to upskill to the intuitive or feeling intelligence level when chatbots can handle routine customer service sufficiently better than human agents and can generate feeling analytics for guiding human agent interactions with customers.

Implications for Consumers

Understand the consumption opportunities and constraints due to the AI-HI complementarity

Compared with marketers, consumers may be less aware of the relative strengths of AI and HI, and resulting in less optimal use of AI for consumption, as reflected in their resistance to use some AI applications even when such use can be beneficial. An example of foregoing the opportunities offered by AI strength is that in some European countries, health and elderly care are provided by robots that can not only monitor and track their health metrics but also can provide companionship for psychological health. Many elders resist such robots due to lack of understanding of their strengths. An example of revealing the limitations of AI in high-tough consumption is evidenced by the social-distanced consumers who are not happy about having social interactions virtually done by AI (e.g., Zoom fatigue) or service provided by AI (e.g., restaurant dine-in replaced by delivery); these AI-dominant feeling tasks scenarios show the value of human interactions and empathy in consumption.

In these consumption scenarios, if consumers can better understand the opportunities and constraints due to the AI-HI complementarity (GP1), they will be able to make more informed consumption decisions about accepting or rejecting AI, and gain control over consumption.

Assist consumption using the right AI

Consumers can benefit from using AI at different intelligence levels. Marketers offer AI products and services, and consumers decide whether they accept or reject. Marketers compete in smart device and application markets for consumers, and consumers need to know what to choose for assisting their consumption. For example, should they choose an Amazon Echo speaker that connects to Alexa only but costs less and is compact, or choose a Sonos One speaker that is compatible with major virtual assistants, has home theater level sound quality, but costs three times more than Echo. Thus, consumers' choice and subsequently their consumption can be augmented based on the set of GP2 principles.

At the mechanical level, use AI for saving time and effort on mechanical consumption tasks. Consumers' time and effort on boring, routine, or undesirable tasks can be saved by using mechanical AI. GP2a suggests that even for mechanical consumption, consumers can benefit from using mechanical AI; for example, various smart self-services (e.g., self-check-in and check-out, kiosks) let consumers take control of when and where to have the service, and smart appliances monitor and inform consumers of their consumption status, freeing consumers from those daily routines to focus on those mechanical consumptions that are contextual, such as working out or dining at a nice restaurant. For example, smart refrigerators with sensors, cameras, and IoT connections can auto-refill consumers' grocery inventory, freeing consumers from boring (and potentially dangerous, in the era of coronavirus) grocery shopping trips. The time saved can be used for (contextual) mechanical activities. On the other side of the coin, consumers should avoid undermining the importance of HI for contextual tasks.

At the thinking level, augment consumption intuition, judgment, and decision. GP2b implies that consumers can augment their consumption intuition by using mechanical and analytical AI applications. In our daily life, we have relied on these two types of AI applications widely, such as using smart vacuum cleaners for house cleaning, and using computers for work and smartphones for life. We are more used to this level of augmentation than the feeling level. An important caveat is to recognize the complementary nature of analytical AI and intuitive HI and leverage this complementarity for better thinking intelligence. For example, a consumer might use the data storage and computing capability of a personal computer to support smart consumption decisions, rather than trying to be a computing machine themselves. Consumers can use smart analytical devices as auxiliary external storage for the brain, and thus the consumer can instead focus on making judgments and decisions. Potential applications for retailing consumers can include using data and analytics enabled by smartphone to monitor impulse buying, control unhealthy eating, or resist left digit pricing (i.e., prices ending in 9, 99 or 95) right in the store.

At the feeling level, augment consumption experiences and emotions. GP2c shows the value for consumers to use AI at various intelligence levels to augment their feeling intelligence. Various AI applications have been used by marketers to understand consumer emotions, and consumers can use AI applications to understand their own emotions and help them manage emotions better as well. For example, consumers may use VR/AR to enhance consumption experience, physiological devices to understand better their emotional reactions to consumption or marketing stimuli, and affective analytics to monitor and inform good consumption behavior, such as a healthy diet. In real-world applications, consumers are using psychological assistant bots to obtain psychological comfort, such as Replika AI that mimics a consumer's style of communication, almost as if the consumer has found the person who knows them the best in the world.

Understand the AI-HI augmentation-replacement duality for delegating consumption tasks

From the consumer's perspective, this duality helps them decide which consumption tasks to delegate to AI and which tasks to be done by themselves. Puntoni et al. (2020) define delegation as when consumers involve an AI solution in performing a task that they would otherwise perform themselves. Following the same two conditions discussed for marketers, in making the task delegation decision, consumers need to consider the intelligence and cost gaps between using AI and using their own labor. Nevertheless, as briefly mentioned earlier, for consumers, the cost aspect can include time and effort spent on a consumption task, in addition to price paid. If the intelligence and cost gaps are tolerable (i.e., consumers can bear the quality or cost difference), consumers should delegate the consumption task to AI, and concentrate on other consumption tasks that consumers themselves can do better (or enjoy more). Fig. 2 illustrates consumption task delegation based this duality using examples at varying intelligence levels.

At the mechanical level, for example, consumers used to use traditional upright vacuum machines to help them do the house cleaning chores, and now they can delegate such cleaning chores fully to robotic vacuums equipped with programming capability to do cleaning autonomously.

At the thinking level, for example, in the early days of e-marketing, many retailers or third-party venders provided price or product comparison services to help consumers choose the right product at the right price, and now many retailers advance to AI recommendation engines that personalize lists of movies, news, or songs for consumers to enjoy without needing them to input selection criteria (i.e., not just provide information for consumers to decide). In this sense, the task of analyzing product information to match consumer preferences is automatically performed by recommendation engines and consumers only need to click to enjoy the movies, news, or songs.

At the feeling level, for example, consumers often rely on online ratings, such as how many stars other consumers have given to a restaurant, or read the reviews about the restaurant to decide which restaurant to eat. Now with advanced machine learning methods to analyze consumers' moods automatically, a facial expression recognition app in a smartphone can recommend to the consumer what to eat, based on a combination of the consumer's mood, weather data, restaurant preference, type, and menu, and geographical distance, freeing the consumer from worrying about what is available to eat, especially when the consumer is in a special mood (e.g., too sad to eat anything). That is, food or restaurant choice has been delegated to AI, incorporating the consumer's mood.

Implications for Researchers

Our general principles represent a starting point for marketing and consumer researchers to explore further how best to optimize, manage, and enhance collaborative intelligence.

AI-HI relative strengths

This general principle has received relatively little research attention, because of the lack of attention to the fact that there are multiple intelligences. The dominant thinking is that there is just one kind of intelligence (thinking, i.e., intelligence quotient (IQ)), and that AI is developed to mimic this thinking intelligence. By contrast, GP1, based on the multiple intelligences view, the computing nature of AI, and the biological nature of HI, points out the need to have more studies on investigating AI-HI relative strengths. A starting point is to recognize this multiplicity of intelligences and investigate their positive and negative uses in marketing and impact on consumption. Specifically:

The relative strengths of AI and HI and the best mix of AI and HI at the macro, meso, and micro levels can be investigated empirically. Macro economy-level analysis provides insights about how the AI-HI relative strengths chance over time, meso firm-level analysis provides insights about how marketers can have the best mix, and micro consumer-level analysis provides insights about how consumers can leverage the AI-HI complementarity for consumption. Rust and Huang (2012) investigated the labor-automation tradeoffs and their long-term effects on productivity due to the advance of technology at the firm level, and more studies are needed for analysis at different levels to understand conditions under which AI and HI can complement each other.

Researchers can also empirically examine consumer reactions to the opportunities and constraints resulting from AI-HI complementarity. Consumer reactions to what AI can do for them can be rational, based on understanding AI strengths and constraints, or irrational, based on misunderstanding about what AI can complement their intellectual capabilities. Examine empirically about how consumers would react to the use of AI at different complementarity scenarios can enhance our understanding about how best for AI to team with consumers.

Exploring innovative ways that the intelligence multiplicity can be used for collaborative intelligence will also be valuable. Both AI and HI have multiple intelligences, which result in their respective relative strengths. Researchers can explore multiple and innovative ways that the multiple intelligences can be used for collaborative intelligence, in addition to the scenarios discussed in this study. For example, text-mining is a strength of analytical AI, but can AI similarly do better than HI for image or video mining? Currently researchers are working on video mining (Li, Shi, and Wang 2019), but further development is needed.

AI-HI collaboration

Marketing researchers have more extensive studies on this type of collaboration, but often do not recognize that there are multiple intelligences, and lower-level AI is best used to augment higher-level HI, rather than the other way around. More studies are needed to investigate how marketing managers can optimize their AI-HI joint workforce, and how consumers can choose the right level of AI intelligence to use. The set of sub-principles of this type of collaboration provides a starting point for researchers to explore, such as how to use mechanical AI for tasks that are undesirable for employees or consumers, how to leverage artificial creativity while avoiding AI bias, and how best to use AI at various intelligence levels to augment consumer experience. Specifically, the following data, models, and topics, related to collaboration at the various intelligence levels, can be addressed:

At the mechanical level, in addressing how to use AI for undesirable employee and consumer tasks, researchers can explore how contextual data can be better captured so that AI's mechanical capability can be enhanced, address the boundary conditions to which mechanical AI can be contextual, examine empirically marketing and consumption task undesirability as the basis of collaboration, and explore qualitatively AI-HI interaction in context for deeper insights about the best way of collaboration. For example, Davenport et al. (2020) consider context awareness as a higher level of AI intelligence than task automation that is currently under development, and may fundamentally change marketing.

At the thinking level, in addressing how to use data and analytical AI to augment intuitive HI, more studies are needed for issues such as exploring the approaches to data and analytical innovation and uncovering the boundary conditions for data and analytical innovation to support human intuition for innovation and creativity (e.g., make the Lexus car AI-scripted commercial strategic). It is also important to investigate the methods for alleviating the current limitations of AI, such as unexplainable, biased, or context-unaware results. The Marchand and Marx (2020) study develops an automated product recommendation method providing actionable explanations, and the Kawaguchi, Uetake, and Watanabe (2019) study investigates the impact of contextual factors (time and crowd pressures) on the effectiveness of AI product recommendation, are two examples in retailing for this effort.

At the feeling level, in addressing how to use AI for better human emotional intelligence, researchers can examine empirically the ability of AI to achieve emotional outcomes, such as engagement, satisfaction, and experience; explore approaches to capturing emotional data and modeling feeling AI (e.g., big emotional data and analytics); conduct scenario experiments or simulations to understand future collaboration scenarios for feelings, which should go beyond measuring consumer reactions to humanoid robots or acceptance of AI; examine how personalization engines can incorporate consumer emotions; and explore sustainable AI that can augment human value.

AI-HI augmentation-replacement duality

This general principle has received the most research attention in management and economics, with the former emphasizing augmentation (e.g., how machines are used to make human workers and organizations more efficient and effective) and the latter emphasizing replacement (e.g., unskilled manufacturing labor replaced by computer automation). We point out that the true decision is typically not choosing between augmentation or replacement, but is more about when to replace (when the gap between AI and HI at a given intelligence level is getting too small).

Thus, for marketing researchers, major research questions will center on managing this duality and examine consequences of this duality on marketing and consumption. Specifically:

Human readiness for AI automation can be investigated empirically. Some consumers are more ready than others. For example, the younger generation may be more technologically ready than older generation, and people-skilled people may be more ready for the Feeling Economy (Huang and Rust 2019; Rust and Huang 2021). The readiness can be about whether AI technologies are mature enough so that marketers and consumers feel that AI is ready, or can be about whether marketers or consumers are psychologically ready to have AI do the jobs. Recently, the Technology Readiness Index (Rockbridge 2020) has begun to monitor this trend over time.

The antecedents and consequences of marketing and consumption tasks that are performed by AI or HI over time can be understood using panel or time series analyses. The time series of these trends help to determine which AI technologies are disruptive and the gaps between AI and HI at the macro level, and the panel data and models can help firms to decide the AI-HI mix based on the intelligence and cost gaps in a given intelligence level and the timing to move up to a higher intelligence level.

The Technology Readiness Index is one empirical example that incorporates these AI time series in its survey at the consumer level.

The AI-HI gaps across intelligence levels, marketing conditions, and consumers for replacement to take place can be measured empirically. How small a gap would be tolerable is unlikely to be universally true across intelligence levels, marketing conditions, and consumers. Thus, the tolerance thresholds need to be investigated empirically taking these factors into consideration. Such investigation can also help to decide what relative strengths are sticker to humans.

Contributions and Conclusions

We develop a framework for collaborative intelligence in marketing, grounded in theory, current and future AI applications, prior and current AI research in marketing, and a multidisciplinary literature. This framework bridges the strategic marketing and technical AI perspectives, and balances the marketer and the consumer perspectives. We explore the ways in which marketers and consumers can use AI collaboratively based on AI-HI relative strengths at different intelligence levels over time, and provide implications for a broad set of stakeholders, including marketers, consumers, and researchers.

References

Antons, David and Christoph F. Breidbach (2018), "Big Data, Big Insights? Advancing Service Innovation and Design with Machine Learning," *Journal of Service Research,* 21 (1), 17–39.

Autor, David (2014), *Polanyi's Paradox and the Shape of Employment Growth,* NBER working paper.

Autor, David H. and David Dorn (2013), "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review,* 103 (5), 1553–97.

Balducci, Bitty and Detelina Marinova (2018), "Unstructured Data in Marketing," *Journal of the Academy of Marketing Science,* 46 (4), 557–90.

Berger, Jonah, Ashlee Humphreys, Stephan Ludwig, Wendy W. Moe, Oded Netzer and David A. Schweidel (2019), "Uniting the Tribes: Using Text for Marketing Insight," *Journal of Marketing,* 84 (1), 1–25.

Chintagunta, Pradeep, Dominique M. Hanssens and John R. Hauser (2016), "Editorial—Marketing Science and Big Data," *Marketing Science,* 35 (3), 341–2.

Cholle, Francis P. (2011), *What is Intuition, and How do We Use It?,* (August 31). Psychology Today. https://www.psychologytoday.com/us/blog/the-intuitive-compass/201108/what-is-intuition-and-how-do-we-use-it

Chung, TuckSiong, Michel Wedel and Roland T. Rust (2016), "Adaptive Personalization Using Social Networks," *Journal of the Academy of Marketing Science,* 44 (1), 66–87.

Chung, TuckSiong, Roland T. Rust and Michel Wedel (2009), "My Mobile Music: An Adaptive Personalization System for Digital Audio Players," *Marketing Science,* 28 (1), 52–68.

Cockburn, Iain M., Rebecca Henderson and Scott Stern (2018), *The Impact of Artificial Intelligence on Innovation,* NBER working paper.

Davenport, Thomas H. and Julia Kirby (2015), "Beyond Automation," *Harvard Business Review,* June, 59–65.

Davenport, Thomas, Abhijit Guha, Dhruv Grewal and Timna Bressgott (2020), "How Artificial Intelligence Will Change the Future of Marketing," *Journal of the Academy of Marketing Science,* 48, 24–42.

Davis, Ernest and Gary Marcus (2015), "Commonsense Reasoning and Commonsense Knowledge in Artificial Intelligence," *Communications of the ACM,* 58 (9), 93–103.

de Bellis, Emanuel and Gita Venkataramani Johar (2020), "Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption," *Journal of Retailing,* 96 (1), 74–87.

Dzyabura, Daria and John R. Hauser (2019), "Recommending Products When Consumers Learn their Preferences Weights," *Marketing Science,* 38 (3), 365–541.

Frey, CarlBenedikt and Michael A. Osborne (2017), "The Future of Employment: How Susceptible Are Jobs to Computerisation?," *Technological Forecasting and Social Change,* 114 (January), 254–80.

Fügener, Andreas, J.örn Grahl, Alok Gupta and Wolf Ketter (2020), *Will Humans-in-the-Loop Become Borgs? Merits and Pitfalls of Working with AI,* Minnesota Friday IS Workshop. April 10.

Gabbott, Mark, Yelena Tsarenko and Wai Hoe Mok (2011), "Emotional Intelligence as a Moderator of Coping Strategies and Service Outcomes in Circumstances of Service Failure," *Journal of Service Research,* 14 (2), 234–48.

Gardner, Howard (1983), *Frames of Mind: The Theory of Multiple Intelligence,* New York: Basic Books.

Gill, Tripat (2020), "Blame It on the Self-Driving Car: How Autonomous Vehicles Can Alter Consumer Morality," *Journal of Consumer Research,* 47 (2), 272–91.

Goleman, Daniel (1996), *Emotional Intelligence: Why It Can Matter More than IQ,* London: Bloomsbury Publishing.

Golembiewski, Lauren (2019), "How Wearable AI Will Amplify Human Intelligence," *Harvard Business Review,* (April), https://hbr.org/2019/04/how-wearable-ai-will-amplify-human-intelligence

Grewal, Dhruv, Anne L. Roggeveen and Jens Nordfalt (2017), "The Future of Retailing," *Journal of Retailing,* 93 (1), 1–6.

Grewal, Dhruv, John Hulland, Praveen K. Kopalle and Elean Karahanna (2020), "The Future of Technology and Marketing: A Multidisciplinary Perspective," *Journal of the Academy of Marketing Science,* 48, 1–8.

Guo, Junpeng, Wenxiang Zhang, Weiguo Fan and Wenhua Li (2018), "Combining Geographical and Social Influences with Deep Learning for Personalized Point-of-Interest Recommendation," *Journal of Management Information Systems,* 35 (4), 1121–53.

Hall, Zachary R., Michael Ahearne and Harish Sujan (2015), "The Importance of Starting Right: The Influence of Accurate Intuition on Performance in Salesperson–Customer Interactions," *Journal of Marketing,* 79 (3), 91–109.

Hartmann, Jochen, Juliana Huppertz, Christina Patricia Schamp and Mark Heitmann (2019), "Comparing Automated Text Classification Methods," *International Journal of Research in Marketing,* 36 (1), 20–38.

Hasford, Jonathan, Blair Kidwell and David M. Hardesty (2018), "Emotional Ability and Associative Learning: How Experiencing and Reasoning about Emotions Impacts Evaluative Conditioning," *Journal of Consumer Research,* 45, 743–60.

Hewett, Kelly, William Rand, Roland T. Rust and Harald van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing,* 80 (3), 1–24.

Hoffman, Donna L. and Thomas P. Novak (2018), "Consumer and Object Experience in the Internet of Things: An Assemblage Theory Approach," *Journal of Consumer Research,* 44 (6), 1178–204.

Huang, Ming-Hui and Roland T. Rust (2018), "Artificial Intelligence in Service," *Journal of Service Research,* 21 (2), 155–72.

——————— and ——————— (2021a), "Engaged to a Robot? The Role of AI in Service," *Journal of Service Research,* 24 (1), 30–41.

——————— and ——————— (2021b), "A Strategic Framework for Artificial Intelligence in Marketing," *Journal of the Academy of Marketing Science,* 49, 30–50.

Huang, Ming-Hui, Roland T. Rust and Vojislav Maksimovic (2019), "The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI)," *California Management Review,* 61 (4), 43–65.

Humphreys, Ashlee and Rebecca Jen-Hui Wang (2018), "Automated Text Analysis for Consumer Research," *Journal of Consumer Research,* 44 (6), 1274–306.

Jarrahi, Mohammad Hossein (2018), "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making," *Business Horizons,* 61 (4), 577–86.

Johnston, Katie (2019), *Netflix and Video Streaming Widen Lead over Subscription TV in Customer Satisfaction, According to the ACSI,* ACSI Telecommunications Report 2018-2019.

Kahneman, Daniel and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision under Risk," *Econometrica,* 47 (2), 263–92.

Kawaguchi, Kohei, Kosuke Uetake and Yasutora Watanabe (2019), "Effectiveness of Product Recommendations Under Time and Crowd Pressures," *Marketing Science,* 38 (2), 253–73.

Kidwell, Blair, Virginie Lopez-Kidwell, Christopher Blocker and Erick M. Mas (2020), "Birds of a Feather Feel Together: Emotional Ability Similarity in Consumer Interactions," *Journal of Consumer Research,* 47, 215–36.

Kim, SeoYoung, Bernd H. Schmitt and Nadia M. Thalmann (2019), "Eliza in the Uncanny Valley: Anthropomorphizing Consumer Robots Increases Their Perceived Warmth but Decreases Liking," *Marketing Letters,* 30 (1), 1–12.

Kleinberg, Jon, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig and Sendhil Mullainathan (2018), "Human Decisions and Machine Predictions," *Quarterly Journal of Economics,* 133 (1), 237–93.

Kurzweil, Ray (2005), *The Singularity is Near,* New York: Viking Press.

Li, Xi, Mengze Shi and Xin Wang (2019), "Video Mining: Measuring Visual Information Using Automatic Methods," *International Journal of Research in Marketing,* 36, 216–31.

Liebman, Elad, Maytal Saar-Tsechansky and Peter Stone (2019), "The Right Music at The Right Time: Adaptive Personalized Playlists based on Sequence Modeling," *MIS Quarterly,* 43 (3), 765–86.

Liedke, Lindsay (2020), *7 Best Marketing Automation Software & Tools to Grow Your Business,* April 15. Bloggingwizard. https://bloggingwizard.com/marketing-automation-tools/

Liu, Jia and Olivier Toubia (2018), "A Semantic Approach for Estimating Consumer Content Preferences from Online Search Queries," *Marketing Science,* 37 (6), 930–52.

Liu, Xiao, Param Vir Singh and Kannan Srinivasan (2016), "A Structured Analysis of Unstructured Big Data by Leveraging Cloud Computing," *Marketing Science,* 35 (3), 363–88.

Longoni, Chiara, Andrea Bonezzi and Carey K. Morewedge (2019), "Resistance to Medical Artificial Intelligence," *Journal of Consumer Research,* 46, 629–50.

Lu, Shasha, Li Xiao and Min Ding (2016), "A Video-Based Automated Recommender (VAR) System for Garments," *Marketing Science,* 35 (3), 484–510.

Luo, Xueming, Siliang Tong, Zheng Fang and Zhe Qu (2019), "Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases," *Marketing Science,* 38 (6), 937–47.

Ma, Shaohui and Robert Fildes (2021), "Retail Sales Forecasting with Meata-Learning," *European Journal of Operational Research,* 288, 111–28.

Malone, Thomas W. (2018), "How Human-Computer 'Superminds' are Redefining the Future of Work," *MIT Sloan Management Review,* 59 (4), 34–41.

Marchand, Andre and Paul Marx (2020), "Automated Product Recommendations with Preference-Based Explanations," *Journal of Retailing,* 96 (3), 328–43.

Mende, Msrtin, Maura L. Scott, Jenny van Doorn, Dhruv Grewal and Ilana Shanks (2019), "Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses," *Journal of Marketing Research,* 56 (4), 535–56.

Misra, Kanishka, Eric M. Schwartz and Jacob Abernethy (2019), "Dynamic Online Pricing with Incomplete Information Using Multiarmed Bandit Experiments," *Marketing Science,* 38 (2), 226–52.

Mohr, Jakki (2020), *Column: Can a Culture of Innovation Co-Exist with a Data-Driven World?,* (March 10). My AMA Daily. https://www.ama.org/marketing-news/column-can-a-culture-of-innovation-co-exist-with-a-data-driven-world/?MessageRunDetailID=1462197049&PostID=12403334&utm_medium=email&utm_source=rasa_io

Neuroscience (2019), *Nature,* https://www.nature.com/subjects/neuroscience

Novak, Thomas P. and Donna L. Hoffman (2019), "Relationship Journeys in the Internet of Things: A New Framework for Understanding Interactions between Consumers and Smart Objects," *Journal of the Academy of Marketing Science,* 47, 216–37.

Ordenes, F. Villarroel, Stephen Ludwig, Ko De Ruyter, Dhruv Grewal and Martin Wetzels (2017), "Unveiling What Is Written in the Stars: Analyzing Explicit, Implicit, and Discourse Patterns of Sentiment in Social Media," *Journal of Consumer Research,* 43 (6), 875–94.

Pavlov, Ivan Petrovich (1960), *Conditional Reflexes,* New York: Dover Publications.

Petit, Olivia, Carlos Velasco and Charles Spence (2019), "Digital Sensory Marketing: Integrating New Technologies into Multisensory Online Experience," *Journal of Interactive Marketing,* 45 (February), 42–61.

Petty, Richard E. and John T. Cacioppo (1986), "The Elaboration Likelihood Model of Persuasion," *Advances in Experimental Social Psychology,* 19, 123–205.

Puntoni, Stefano, Rebecca Walker Reczek, Markus Giesler and Simona Botti (2020), "Consumers and Artificial Intelligence: An Experiential Perspective," *Journal of Marketing,*, http://dx.doi.org/10.1177/0022242970951847

Raisch, Sebastian and Sebastian Krakowski (2020), "Artificial Intelligence and Management: The Automation-Augmentation Paradox," *Academy of Management Review,*, http://dx.doi.org/10.5465/2018.0072

Russell, Stuart J. and Peter Norvig (2009), *Artificial Intelligence: A Modern Approach,* 3rd ed. Upper Saddle River: Prentice Hall.

Rust, Roland T. and Ming-Hui Huang (2014), "The Service Revolution and the Transformation of Marketing Science," *Marketing Science,* 33 (2), 206–21.

——— and ——— (2021), *The Feeling Economy: How Artificial Intelligence Is Creating the Era of Empathy,* Palgrave-Macmillan.

Rust, Roland T., William Rand, Ming-Hui Huang, Andrew T. Stephen, Gillian Brooks and Timur Chabuk (2020), *A Brand Reputation Tracker Using Social Media,* Working paper.

Shim, Jung P., Joon Koh, Steven Fister and H.Y. Seo (2016), "Phonetic Analytics Technology and Big Data: Real-World Cases," *Communications of the ACM,* 59 (2), 84–90.

Skinner, BurrhusFrederic (1938), *The Behavior of Organisms: An Experimental Analysis,* Oxford: Appleton-Century.

Sutton, Dave (2018), "How AI Helped One Retailer Reach New Customers," *Harvard Business Review,* (May), https://hbr.org/2018/05/how-ai-helped-one-retailer-reach-new-customers

Tirunillai, Seshadri and Gerard J. Tellis (2012), "Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance," *Marketing Science,* 31 (2), 198–215.

van Doorn, Jenny, Martin Mende, Stephanie Noble, John Hulland, Amy Ostrom, Dhruv Grewal and A. Petersen (2017), "Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences," *Journal of Service Research,* 20 (1), 43–58.

Voss, Glenn B. and ZannieGiraud Voss (2000), "Strategic Orientation and Firm Performance in An Artistic Environment," *Journal of Marketing,* 64 (1), 67–83.

Wedel, Michel and P.K. Kannan (2016), "Marketing Analytics for Data-Rich Environments," *Journal of Marketing,* 80 (6), 97–121.

Wirtz, Jochen, Paul G. Patterson, Werner H. Kunz, Thorsten Gruber, Lu Vinh Nhat, Stefanie Paluch and Antje Martins (2018), "Brave New World: Service Robots in the Frontline," *Journal of Service Management,* 29 (5), 907–31.

Wright, Peter (2002), "Marketplace Metacognition and Social Intelligence," *Journal of Consumer Research,* 28 (March), 677–82.

Yuan, Lingyao(Ivy) and Alan R. Dennis (2019), "Acting Like Humans? Anthropomorphism and Consumer's Willingness to Pay in Electronic Commerce," *Journal of Management Information Systems,* 36 (2), 450–77.