

# “How artificial intelligence can change the core of marketing theory”

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# HOW ARTIFICIAL INTELLIGENCE CAN CHANGE THE CORE OF MARKETING THEORY

## Abstract

Various recently-introduced applications of artificial intelligence (AI) operate at the interface between businesses and consumers. This paper looks at whether these innovations have relevant implications for marketing theory. The latest literature on the connection between AI and marketing has emphasized a great variety of AI applications that qualify this relationship. Based on these studies but focusing only on the applications with a direct impact on the relationship at the very heart of marketing, i.e., the one between firms and consumers, the paper analyzes three categories of AI applications: AI-based shipping-then-shopping, AI-based service robots, and AI-based smart products and domestic robots. The main result of this first analysis is that all three categories have to do, each in their own way, with mass customization. A discussion of this common trait leads us to recognize their ways to mass customization that – unlike the traditional approach developed thanks to flexible automation and product modularity technologies – place the customization process within a broader perspective of consumer needs management. This change in approach means that marketing should focus more on managing consumers' needs than directly on the satisfaction of those needs. This finding marks a genuine discontinuity that opens up a new space for reflection for scholars and marketing managers alike.

## Keywords

shipping-then-shopping model, service robots, domestic robots, smart products, mass customization

## JEL Classification

M15, M31, O33

## INTRODUCTION

Artificial intelligence (AI) will change the way we conceive and conduct marketing. This was predicted already in the 1980s, especially regarding the development of marketing decision support systems (Lillis & McIvor, 1985; Wierenga & Oude Ouphuis, 1997). However, this prediction did not come true if about a decade ago – in the authoritative opinion voiced by Berend Wierenga (2010) – the domains of AI applications and of marketing managers' real-life decision-making were still almost completely disjointed.

In recent years, interest in AI and its impact on marketing – and particularly on the marketing of consumer goods and services – has regained momentum. Once again, there is talk of radical changes underway, but this time they are no longer limited to the area of marketing decisions but embrace a considerably wider horizon. Are we again showing signs of excessive optimism regarding AI? For several reasons, we are inclined to believe quite the opposite. To start with, there have been considerable advances in the capabilities of AI in recent times that can be crucially important in marketing because they concern natural language processing, image recognition, speech recognition, problem-solving, and machine learning (Davenport et al., 2020; Kietzmann, Paschen, & Treen, 2018). Second, the capillary use of the Internet and smartphones has hugely increased the amount of

information generated by consumers that feed AI systems (Fan, Ning, & Deng, 2020; Schwab, 2017). AI is also part of a wider process that is called the fourth industrial revolution (or digital transformation, industry 4.0), which has several complementary components – including the Internet of Things (IoT) – that are co-evolving (Ustundag & Cevikcan, 2018). Then, we must not forget that several AI applications for the field of marketing have already been tested successfully by pioneering firms, be they incumbents or newly formed (Davenport et al., 2020; Marr & Ward, 2019).

The latest literature on the connection between AI and marketing has emphasized a great variety of AI applications that qualify this relationship (Davenport et al., 2020; Kietzmann et al., 2018; Kumar et al., 2019; Steinhoff et al., 2019; Sterne, 2017). Many of these applications are specifically designed to support marketing management activities, enabling even considerable improvements in their performance, in terms of efficiency and efficacy. The whole spectrum of traditional marketing management activities is affected by the development of AI, from demand forecasting to post-purchase services. Without underestimating the importance of these developments, the present contribution focuses only on the applications directly impacting the relationship at the very heart of marketing, i.e., the one between firms and consumers. These applications might have important implications for the theoretical edifice of marketing, and this paper aims to find out whether this is the case of the “new” AI.

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## 1. LITERATURE REVIEW

From the literature mentioned above, various AI applications interfacing with consumers can be identified. For the analysis, they are placed in three categories: AI-based shipping-then-shopping, AI-based service robots, and AI-based smart products and domestic robots. This section discusses each of these categories of AI applications.

### 1.1. The shipping-then-shopping model

In traditional brick-and-mortar and online retail experiences, the purchasing process is completed with the product’s transfer to the consumer’s home. But the founder of Stitch Fix, a multi-brand e-tailer of fashion articles, has reversed the sequence. Katrina Lake defines the business model she has invented as straightforward: “We send you clothing and accessories we think you’ll like; you keep the items you want and send the others back” (Lake, 2018, p. 35). Of course, guessing what consumers will like (something that the company has succeeded in doing, as its sales demonstrate) is far from easy. First of all, there is a proprietary AI system that uses a large body of information to select a set of five articles to put into each Fix shipment. This information is provided largely by customers who answer a detailed questionnaire about their style, size, and price preferences (which can be indicated using a table format), plus images or other

non-numerical data about themselves (from customers’ Pinterest pages and likes). Other information is drawn particularly from the Stitch Fix company’s now very large client portfolio. For an article notoriously hard to fit like jeans, for instance, “the algorithms are able to select for each customer a variety of jeans that other customers with similar measurements decided to keep” (Malone, 2018, p. 37). After each shipment, customers also provide informative feedback that the system uses to improve its picks over time (Lake, 2018; Luce, 2019). However, the preparation of a customized set of articles is not just down to the work of algorithms. The last word always goes to human stylists who can relate to consumers in a more personal way (Malone, 2018). Their intervention justifies that if a customer does not keep any of the articles in a shipment, they still pay \$20.

The art of offering potential customers something capable of satisfying their wishes and expectations is as old as commerce and is still practiced by sales assistants in traditional shops. What is much more recent is the evolution of this practice into a menswear subscription service revolving around the interaction between stylists and customers, as proposed by Trunk Club (founded in 2009) on its company website and in its brick-and-mortar shops (Tao & Xu, 2018). Two such major e-tailers as Amazon and Netflix had previously started their services for providing customers with purchasing recommendations (Shen, 2014).

Drawing on these experiences, Stitch Fix (founded in 2011) went a significant step further in its shipping-then-shopping model by combining a sophisticated and complex AI system with the work of human stylists. The company's extraordinary success prompted other businesses in the fashion world, including Trunk Club (Modi & Zhao, 2019), to move in the same direction – with very different performance (Davenport et al., 2020). It is probably still too early to draw any conclusions from these experiences. However, at least one general lesson can be learned from the most successful cases: AI can be the cognitive engine of an original tailored approach to the consumer that is capable of achieving high levels of customer satisfaction and loyalty (Davenport et al., 2020).

The fact that a shipping-then-shopping model, even in its AI version, was conceived and developed in the fashion sector might lead us to think that it may have particular features that make it unsuitable for use in other sectors. Such an assumption does not seem to hold when considering that the idea of offering personal recommendations on the strength of previous online purchases was not born in the fashion industry. Amazon is currently developing various projects in the field of “anticipatory shipping” (Marr & Ward, 2019).

## 1.2. Service robots

Robots or cobots (collaborative robots), as they are sometimes called, are already spreading in factories and elsewhere along the logistic chain. For instance, in Amazon warehouses, they deliver merchandise to employees for packaging and shipment (Daugherty & Wilson, 2018). From the warehouses, the goods then go directly to consumers (as in the case of Amazon), or retailers' shops. Robots have made their appearance in retailing too, standing behind frontline employees, or interfacing directly with customers visiting the shop. The prospects for growth in both these applications of robotics in shops seem very promising (Bogue, 2019). In the former case (robots helping employees), the growing tendency for people to purchase items online and pick them up in-store is perfectly suited to the presence of in-store robots that know exactly where to find every product and the optimal picking route (Bogue, 2019). As for the second type of robots (that help customers), the ability to inter-

act with customers is a distinctive trait of a new generation of robots destined to replace or work alongside human employees (Belanche et al., 2020; Wirtz et al., 2018). A frequently-mentioned case is the LoweBot, a service robot introduced in 2016 by a retailer specializing in home improvements. It helps customers to find products and can answer simple questions. It also assists employees in identifying low stock levels, for instance, or misplaced items (Bogue, 2019; Larivière et al., 2017).

Service robots are being tested not only in shops but also in other service delivery contexts. Some robots can serve as coffee baristas or restaurant waiters (Davenport et al., 2020; Fan et al., 2020), and robots at the reception desk in hotels or museums (Wirtz et al., 2018). Robots are assisting child patrons in public libraries (Lin et al., 2014), and healthcare robots are now used in various hospitals (Pee, Pan, & Cui, 2019; van Wynsberghe, 2016).

Focusing on frontline services, Wirtz et al. (2018, p. 909) defined service robots as “system-based autonomous and adaptable interfaces that interact, communicate, and deliver service to an organization's customers”. This definition underscores the evolutionary leap that robots made as soon as they were fitted with AI. They can now perform complex series of actions and analyze data, learn and make autonomous decisions, adapt, and customize their services (starting by recognizing a customer). The information they use to do their job comes from incorporated devices (cameras, microphones, and sensors), from sources within the organization where they operate (in particular, its customer database), and – increasingly in future – from outside sources. Wirtz et al. (2018) also emphasize the social dimension of AI-based service robots as they represent the counterpart in the interaction with a customer. As van Doorn et al. (2017, p. 43) illustrate with the concept of automated social presence, their social skills may be more or less well developed, meaning “the extent to which technology makes customers feel the presence of another social entity”.

The definition of service robots suggested by Wirtz et al. (2018) is very broad. It embraces frontline service robots in the strict sense (the topic of this section) – which may have anthropomorphic physical features, or they may not (as in the case

of the previously-mentioned LoweBot) – and any other frontline service technology (De Keyser et al., 2019), whether it is a real frontline presence or a virtual one (as in the case of AI customer assistance software working independently and learning over time). However, virtual assistants are classified as service robots, which unavoidably creates a certain overlap with the type of applications discussed in the previous section. For instance, a virtual style assistant like Amazon's Echo Look is clearly inspired by the Stitch Fix experience (Luce, 2019).

Service robots can completely replace frontline employees or else work behind or alongside them (Robinson et al., 2019). The main factor driving the diffusion of robots instead of employees is to obtain cost savings for the firm (De Keyser et al., 2019). Alternatively, robots can augment the service provided by frontline employees, helping them to do their job better (De Keyser et al., 2019; Larivière et al., 2017; Marinova et al., 2017). That said, the substitution versus augmentation dichotomy fails to cover the case where robots take over from employees in directly interacting with customers so that the same employees can do something else, or do their normal job differently, or better. This division of labor characterizes the case of LoweBot, for instance: as the company emphasizes on its Lowe's Innovation Labs site: "As LoweBot helps customers with simple questions, it enables employees to spend more time offering their expertise and specialty knowledge to customers". Some authors have pointed out that such a joint and complementary presence of robots and employees is a factor that favors the customers' acceptance of the robots (Davenport et al., 2020). There is clear empirical evidence of this aspect in the hospital sector (Longoni, Bonezzi, & Morewedge, 2019).

### 1.3. Smart products and domestic robots

Intelligent products and smart products are terms that can be used interchangeably (Meyer, Främling, & Holmström., 2019), though the domains in which the former is used are mainly in manufacturing and supply chains, while the latter is used more to refer to the use that consumers make of such products. While intelligent

or smart products may be more or less intelligent, as Meyer et al. (2009) remind us, there is no doubt that their average level of intelligence has increased thanks to recent advances in AI, and so has the opportunity to incorporate them in artifacts and products, and this trend will continue (Tomiyama et al., 2019). Firms in every sector are integrating AI in their products to make what they have to offer their customers more compelling (Porter & Heppelmann, 2014). Examples are BMW, Tesla, and Volvo in the automotive industry (Marr & Ward, 2019), supported by software companies like Affectiva (Davenport et al., 2020). Even the voice assistants already on the market for years, starting from Apple's pioneering Siri, can be defined as smart products (Kaplan & Haenlein, 2019; McLean & Osei-Frimpong, 2019).

Embedding AI in a product enables it to be context-aware, to adapt to particular situations, and especially to different users and other products. Using data obtained from the environment, smart products "take action" independently, and even proactively (Maass & Varshney, 2008). Given these characteristics, and considering these products as service-providing platforms (Vargo & Lusch, 2004), the services that smart products can provide are highly customizable (Kumar et al., 2019). Smart products also learn from experiences in which they are involved and, with time, this improves the alignment between their actions and the degree of customization they can achieve.

The broad category of smart products also includes domestic robots that cater for various needs associated with domestic life nowadays. There are robotic vacuum cleaners and other kinds of cleaning robots, robots that do garden maintenance and laundry, and companion robots such as those used in caring for the elderly (Bogue, 2017; Čaić, Odekerken-Schröder, & Mahr, 2018). These robots are essentially no different from the frontline service robots discussed previously, apart from the different contexts in which the former and latter provide their services. On the other hand, the resemblance between the two types of robots will make their respective usage contexts similar. In the case of domestic robots too, AI has proved a formida-

ble lever for departing from the past, when single-function robots could perform a very limited set of tasks (Bogue, 2017). Their improvement, in terms of their smartness and the extension of what they can do, makes it easy to predict a strong increase in the diffusion of domestic robots in the future. Their popularity may even parallel that of service robots, though the issues that interfere with consumers' acceptance of either type of device should not be underestimated (Davenport et al., 2020; Sohn & Kwon, 2020).

Smart products and domestic robots, frontline service robots, and various other frontline service devices are all smart objects. Their ability to enter into a relationship with people and other objects is an indispensable component of their intelligence. Smart objects are the "things" of the Internet of Things (IoT). Smart objects and the IoT "are two ideas which describe the future, walk together, and complement each other" (García et al., 2017, p. 7).

## 2. GENERALIZATION OF THE MAIN STATEMENTS

A cross-analysis of the categories of AI applications described above leads us to acknowledge a dimension that they share: each in their own way, they all have to do with mass customization, in the sense of capability to offer individually tailored products or services on a large scale (Gilmore & Pine, 2000; Zipkin, 2001). Whether in AI-based robots and products or the shipping-then-shopping model, customization is achieved through the interaction between an artifact (robot, product, software) and a consumer. It is worth noting that the system pioneered by Stitch Fix lies midway between "customization" and "personalization", according to the distinction drawn by Arora et al. (2008): the latter is involved when firms decide which products are suitable for given individual consumers, basing their decision on previously-collected customer data; the former when consumers actively specify what product they want. Interestingly, Arora et al. (2008) mention as a very popular example of personalization the collaborative filtering used by Amazon to establish what music or

books to recommend to its customers. As it was seen, Stitch Fix revisited this and other experiences, developing a model that more closely resembles customization proper. Exploiting the information exchanged between the business and the customer, the resulting objectively-tailored product assortment is the outcome of a co-specification. The part played by the customer is partly active, and partly passive or unwitting.

At the end of the last century, the third industrial revolution – based on flexible automation or flexible manufacturing, and product modularity – paved the way to mass customization, i.e., to an appropriate variety and, at the same time, accessible to a large number of consumers (Feitzinger & Lee, 1997; Pine, 1993). In contrast with the mass production paradigm based on standardized products sold at prices that everyone can afford, mass customization succeeds in making product variety inexpensive "so that nearly everyone finds exactly what he or she wants at a reasonable price" (Kotha, 1994, p. 22). Over time, mass customization strategies have come to rely on sophisticated web-based product configuration systems (Fogliatto et al., 2012). Looking at the results achieved along the technological path to mass customization, it should be said that the promised encounter between the variety offered by firms and the variety demanded by consumers had been only partially successful (Franke, 2009; Haug et al., 2012; Matzler et al., 2007; Tiihonen & Felfernig, 2017; Zipkin, 2001). Among the reasons for this, what interests us most for the analysis concerns the previously-quoted phrase "*what he or she wants*" since consumers may not know exactly what they want (Franke, 2009; Kramer, 2007; Simonson, 2005; Syam et al., 2008; Zipkin, 2001). When this happens, the elicitation mechanisms developed by firms to obtain precise information from their customers cannot function properly. This gives rise, on the demand side, to a problem of preference specification or preference construction (Kramer, 2007) such that it becomes objectively difficult on the supply side (the seller in a brick-and-mortar store, or the software of a manufacturer or a retailer in the online sales of customized products) to offer solutions that customers will judge suited to their needs at the time of their consumption.

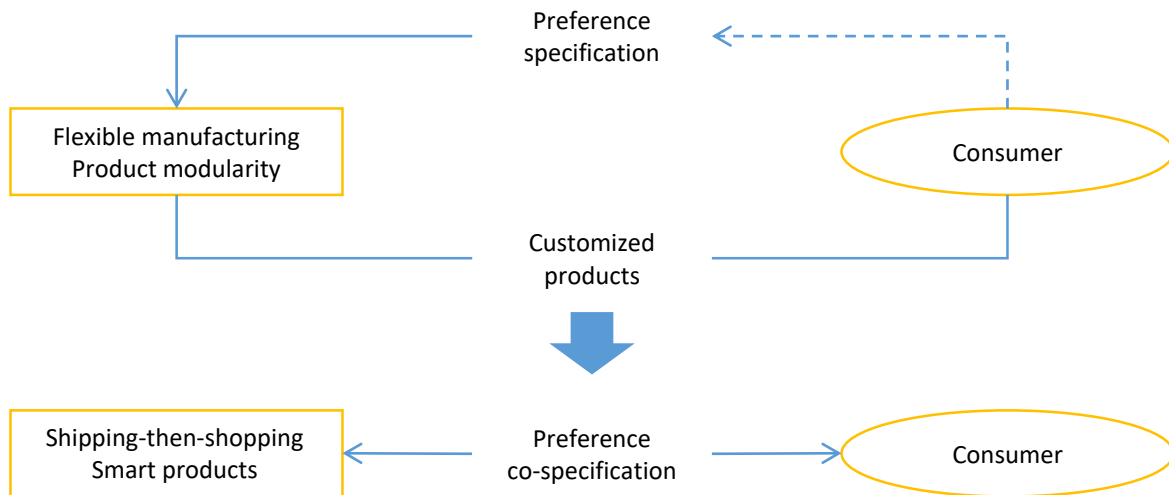
The problem of preference specification can be managed by interacting with the customer, as emphasized in marketing studies that – in the wake of the contribution from Peppers and Rogers (1993) – have seen mass customization and one-to-one marketing as two sides of the same coin. A good interaction with the customer triggers and supports a shared preference construction process, thereby clarifying the customer’s initial ideas (Simonson, 2005). This process is unavoidably costly for the business and affects the price of the products being customized. In other words, the more mass customization has to rely on this interaction, the more the “mass” part of the oxymoron is diluted. Consumers may find the interaction costly as well (Dellaert & Stremersch, 2005; Matzler et al., 2007; Tiihonen & Felfernig, 2017), but they will be more willing to spend their time on the interaction if the consumer experiences the process designed by the firm as an experience sufficiently gratifying and emotionally enriching (Addis & Holbrook, 2002; Di Bernardo and Grandinetti, 2012; Fan et al., 2020; Franke & Schreier, 2010; Teichmann et al., 2016). Be that as it may, there is still an unavoidable structural element of uncertainty due to the unconscious dimension behind consumer behavior (Martin & Morich, 2011), which may negatively influence the consumer’s final judgment, making the interaction effort pointless.

In its more advanced versions, the shipping-then-shopping model takes effect precisely on this element of uncertainty. It improves the efficacy (and efficiency) of the mass customization process by using AI algorithms to analyze information not explicitly provided by the consumer; relying on a broad and constantly expanding specific numerical and non-numerical database for a given consumer, which can be compared with other consumers’ data; and involving high-level professionals (such as fashion stylists) on a large scale. At the same time, this model tends to involve consumers on an emotional level, immersing them in a globally gratifying experience (Tao & Xu, 2018). It is worth noting that the customization and associated co-specification of preferences take shape differently in the shipping-then-shopping model vis-à-vis the traditional mass customization approach (Figure 1). The latter involves a flexible and modular production of goods and services, the former entails selecting from a vast, but still giv-

en range of products. However, these two methods seem capable of contaminating one another. On the one hand, a shipping-then-shopping strategy can also include products customized according to the traditional mass customization approach in the range it offers. On the other hand, the efficacy of customization based on product configurators might be improved by experimenting with new AI-based approaches in the wake of what has been achieved using the shipping-then-shopping model (Tiihonen & Felfernig, 2017). More in general, the association between AI and customization looks like an area worth exploring that is likely to generate new and original developments.

While the shipping-then-shopping model and, in future, also product configurators (once the use of AI has made them smarter) change the traditional approach to mass customization, the AI-based evolution of service robots will entrain some of the services traditionally provided by frontline personnel into the sphere of mass customization. In a sense, one could speak of service industrialization, but this is a very different phenomenon from what was seen in the past (Levitt, 1976) (Figure 2). In fact, it was seen from the studies mentioned in a previous section that, in known and predictable experimental settings, AI-based service robots: (1) do not lead to a McDonaldization of the services with a corresponding loss of flexibility and customization; (2) have the advantage of never becoming impatient, as frontline employees sometimes do; (3) can draw on a stock of knowledge far exceeding that of even the most expert employee at the interface with the customer; and (4) may not necessarily replace, but serve instead in a complementary role alongside human employees, and this sharing of the workload strengthens the level and quality of the customization made available to consumers. It is also worth noting that these characteristics are identifiable in the shipping-then-shopping model as well (and in product configurators) insofar as they are considered as customized services for supporting the customization of products (goods), and compared with similar services provided by sales personnel in brick-and-mortar shops.

The third category of AI applications considered here includes smart products and domestic robots, which share the feature of being used by consum-



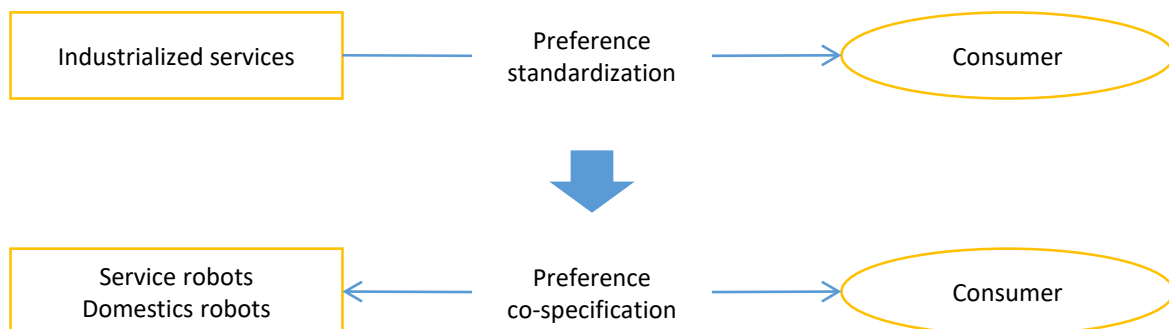
**Figure 1.** From traditional to AI-based mass customization

ers in their own homes or elsewhere, places different from those managed by service organizations. However, to examine mass customization, it is useful to consider the two groups separately. As mentioned earlier, there are no substantial technological differences between domestic robots and service robots, which is also true for mass customization. While service robots extend the domain of mass customization to services provided by frontline personnel, domestic robots extend it to services provided by consumers themselves (self-service), or by their domestic workers. Smart products, on the other hand, can be more useful than products obtained using the traditional approach to mass customization (Figure 1). In the latter case, all customization is completed, once and for all, in the interaction preceding the purchase, whereas smart products manage the customization directly and interactively, during their usage, and the outcome is variable. Consider, for example, the products that adapt ergonomical-

ly to certain physical characteristics of their user, adjusting to different use situations or changing in the individual. While making products with a potential for customization is not new (Gilmore & Pine, 1997; Zipkin, 2001), the idea of doing so with AI is setting the stage for something entirely novel (Kumar et al., 2019). Intriguingly, there can be seen much the same connection between smart products and the shipping-then-shopping model as concerns the preference specification process. In both cases, this process takes place effectively thanks to the cognitive capacity of AI, and to the information provided by the consumer.

### 3. DISCUSSION

The analysis suggests that the novel association between AI and marketing artifacts (products, robots, software) induces mass customization to move away from the ancillary role to which it had



**Figure 2.** From traditional to AI-based service industrialization



been relegated, and occupy the very heart of the theory and practice of marketing. Following this shift, the goal of marketing would focus less on directly *satisfying* consumers' needs, as still stated in current definitions of marketing (e.g., Baker, 2014; Kotler & Armstrong, 2018) – where these needs are elements exogenous to the marketing process (and are unambiguous as far as the consumer is concerned) – and more on *managing* consumers' needs to ensure their satisfaction. Thus, the marketing process becomes a needs management process, and this is precisely what is customized with the help of intelligent interfaces (products, robots, software) capable of interacting with the consumers' intelligence. Needs management and (mass) customization thus become key marketing constructs.

If the phenomena described above continue to develop and spread, the advent of the needs management perspective would bring a “Copernican” revolution in the world of marketing. It would be no less game-changing than the transition in the last century when firms' approach to the market switched from focusing on sales to marketing in the modern sense of the word (Kotler, 1965; Levitt, 1960). Moving along this path, the concept of preference construction – as discussed in a specific line of research (Warren et al., 2011) – can serve us well as a core element of the new theoretical building of marketing, much more important than it might seem today in the existing framework.

This genuine discontinuity opens up a new space for reflection for scholars and marketing managers alike. Taking this view, it would seem reasonable to say, as some authors have done already (reviewed by Kaartemo & Helkkula, 2018), that AI applications in the world of marketing supply new lymph to the value co-creation processes made popular by the value co-creation theory of Prahalad and Ramaswamy (2004), and the service-dominant logic of Vargo and Lusch (2004). However, if we were to remain on this plane, we would be unable to grasp the discontinuity that our analysis has identified. In other words, considering the two parts of the value co-creation process, the current (and future) use of AI gives the offering part far more cognitive capacity and power than in the past, on the strength of which they can set themselves the ambitious goal of man-

aging consumers' particular needs. The obvious, strong asymmetry between firms and consumers prompted by the former's use of AI is a new, robust argument supporting the suggestion advanced by Cova et al. (2011) that the concept of value co-creation is approached more cautiously and critically than has been done to date in the literature on management and marketing.

While it is hard to imagine the revolution promised by modern AI not happening, as it was said in the introduction to this paper, it is also important to bear in mind that this will be a “slow” revolution (Davenport, 2018). Two factors combine to make it so, one on the supply side, and one on the demand side. On the supply side, much research and experimental work remain to be done before the “normal” level of intelligence associated with AI applications that interact with consumers achieves a full context awareness, i.e., when they can “address complex, idiosyncratic tasks by applying holistic thinking and context-specific responses” (Davenport et al., 2020, p. 27). On the demand side, consumers have reservations about AI that negatively affect their propensity to make use of its applications. This attitude stems partly from the feeling that such technologies neglect their uniqueness (Davenport et al., 2020; Longoni et al., 2019), an aspect goes hand in hand with the problem mentioned above on the supply side. Then, no less important is the fact that consumers worry about their privacy (Davenport et al., 2020; McLean & Osei-Frimpong, 2019; Pagallo, 2013). This second problem is intrinsic: consumers must provide the personal details on which AI applications rely, as discussed earlier, in exchange for customization. In the case of online customized advertising, such a trade-off has triggered a debate on the privacy-personalization paradox (Aguirre et al., 2015).

On both sides, the situation is still developing. As concerns the technologies and AI systems, the direction taken by innovation efforts is clearly towards context awareness, as mentioned in various pioneering experiences (Davenport et al., 2020; Huang & Rust, 2018). Moreover, the cognitive capacity that AI applications can deploy at the interface with consumers is gaining strength as they co-evolve with other components of the fourth industrial revolution. In the case of coupling AI with the

IoT, suffice it to mention as an example the chance to connect service robots of the same type (Wirtz et al., 2018). On the demand side, consumers' reservations about their privacy are well-founded and pose the problem, yet to be solved by policymakers, of how to control who manage large amounts of personal data (Davenport et al., 2020; Horvitz & Mulligan, 2015). That said, if simply looking at the paradox between privacy and customization, it is reasonable to expect that consumers who appreciate the benefits of AI-based customization will come to trust the other party, defusing the paradox as a result. This can only happen if effective customization counts for the consumer. A recent, important work by Longoni et al. (2019) on the use of healthcare services provided by AI suggests

that this is, in fact, the case. The authors demonstrate that consumers resist these services because they think an AI provider (such as a robot) is less able than a human provider to take their unique characteristics and circumstances into account. However, their reluctance fades when AI provides healthcare that is presented as customized. These empirical results bring us back to the association between the concepts of mass customization and need management emerging from the analysis. For organizations wishing to embark on the "high road" to AI, taking the needs management perspective, a crucial and specific part of their marketing strategy will have to focus on communicating the customization process in which they wish to involve consumers transparently and effectively.

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## CONCLUSION

This paper attempts to shed light on whether the new season of AI applications in organizations offering consumer goods and services has elements of novelty sufficient to have important implications from the point of view of marketing theory. For this purpose, the analysis focused on three categories of AI applications that operate at the interface between businesses and their customers: AI-based shipping-then-shopping; AI-based service robots; and AI-based smart products and domestic robots.

Looking at the very different applications of AI in these three categories, and how they operate, it was seen that they all have to do with mass customization. To be more precise, they are ways to mass customization that, unlike the traditional approach (which developed thanks to the technologies of the third industrial revolution), set the customization process proper in a broader perspective of managing consumers' needs. This also means managing consumers' partial ignorance of what is involved and their uncertainties too. In short, the focus of marketing should be on managing the needs rather than on its outcome, namely their satisfaction.

## AUTHOR CONTRIBUTIONS

Conceptualization: Roberto Grandinetti.

Data curation: Roberto Grandinetti.

Formal analysis: Roberto Grandinetti.

Funding acquisition: Roberto Grandinetti.

Investigation: Roberto Grandinetti.

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