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Brave New World? On AI and the Management of Customer Relationships

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Abstract

In light of the emerging discourse on AI systems' effect on society, whose perception swings widely between utopian and dystopian, we conduct herein a critical analysis of how artificial intelligence (AI) affects the essential nature of customer relationship management (CRM). To do so, we survey the AI capabilities that will transform CRM into AI-CRM and examine how the transformation will influence customer acquisition, development, and retention. We highlight in particular how AI-CRM's improving ability to predict customer lifetime value will generate an inexorable rise in implementing adapted treatment of customers, leading to greater customer prioritization and service discrimination in markets. We further consider the consequences for firms and the challenges to regulators.

Keywords: Artificial intelligence; Customer relationships; Customer lifetime value; Customer Prioritization; CRM; Regulation

To a great extent, the CRM revolution that took off in the 1990s depended upon technology. Input and storage technologies enabled firms to start collecting and storing data on individual customers, and thereafter to analyze customers' profitability over time (Blattberg, Glazer, & Little, 1994), while smarter manufacturing systems promised mass customization (Gilmore & Pine, 1997). Research done by leading consulting firms cited the role of the retention rate—until then, an infrequently used measure—as a significant driver of a firm's profitability (Reichheld & Sasser, 1990). With the first wave of the rise in data collection, storage, and analysis abilities, marketers began taking a customer lifetime value approach to managing customers (Berger & Nasr, 1998; Gupta & Lehmann, 2003).

Technology infusion into relationship management continues apace: Information technology and advanced analytics support ubiquitous customer communication and increasing availability of customer data, in turn enabling firms to offer personalized services and curating customer relationships to grow more profitable customers (Rust & Huang, 2014; Gupta, Leszkiewicz, Kumar, Bijmolt, & Potapov, 2020 this issue). At the center of marketers' attention in this regard are the emerging technologies of *artificial intelligence (AI),* which refer to "a system's ability to *correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"* (Kaplan & Haenlein, 2019, p. 15). In

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the context of customer relationship management, these technologies enable firms to analyze data and interact with consumers faster and on a larger scale. In the longer term, enabling human-like interactions between AI-driven systems and customers will allow the provision of widespread personalized services at low cost, possibly altering the nature of customer service as they do so (Kaplan & Haenlein, 2019; Hoyer, Kroschke, Schmitt, Kraume, & Shankar, 2020 this issue; Grewal, Kroschke, Mende, Roggeveen, & Scott, 2020 this issue). Combining the two notions of AI and CRM, we suggest that *any CRM system exhibiting sufficiently flexible adaptation can be labeled an artificially intelligent CRM system or AI-CRM.*

Our aim in this article is to examine AI systems' fundamental effects on how firms manage their relationships with their customers. There has been burgeoning discussion, in a plethora of recent publications, of the expected development of AI systems, their future ability to replace humans, and the specifics of the technologies that fall under the rubric “AI” (Agrawal, Gans, & Goldfarb, 2018; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019). Some of this work is customer-related and has focused on the expected change in the nature of customer service (Huang & Rust, 2018; Kumar, Bhagwat, & Zhang, 2015). While we touch on some of these areas, our aim here is not to conduct another review of this topic. Instead, our focus is on the broader implications of the effects of AI-CRM on the nature of customer relationships, and in particular, the outcomes for customers and other stakeholders.

The discourse on AI systems' effect on society swings wildly between utopian and dystopian (Friend, 2018; Tegmark, 2017). Some experts cite smart machines' ability to enable individuals to have more leisure time, choose not to work at all, and enjoy longer life expectancy. Others raise the potential of massive job losses (mainly among relatively disadvantaged population segments), a fear that the machines will “take over from humans,” and an increase in disparity as the less affluent members of society are last in line to enjoy the fruits of AI (Agrawal, Gans, & Goldfarb, 2019).

In terms of customer management, the overall sentiment seems positive. While there is a question of a rise in job losses in the increasingly automated service sector (West, 2018), the emergence of AI tools is perceived as beneficial to all facets of the customer relationship management process: making it easier for consumers to obtain more personalized goods and services while at the same time increasing firms' profitability (Kumar, Rajan, Venkatesan, & Lecinski, 2019; Rust & Huang, 2014; Gupta et al., 2020 this issue). Yet despite the rosy picture in the marketing literature, questions remain as to the fate of customers in an AI-driven future.

Essentially, AI-CRM systems driven by machine learning and its successor technologies will enable managers to make improved predictions based on large quantities of collected data (Agrawal et al., 2019). This means a de facto better estimation of future individual transactions (which is to say, Customer Lifetime Value, or CLV) along with improved ability to create individual-level granular price and quality discrimination designed to increase firms' profits and reduce (or even eliminate) consumer surplus. As we will discuss, the improved ability to target and discriminate among individuals based on real-time data will likely contribute to increasing social inequality (Wertenbroch, 2019). At the same time, the loss of consumer autonomy in the age of AI (André et al., 2018) may result in reduced consumer perception of being manipulated or discriminated against.

In this article, we conduct a critical examination of how AI systems may affect the basic nature of customer relationship management. In particular, we focus on how AI's emerging abilities to manage customer relationships may result in differential treatment of customers and the implications thereof. Enhanced personalization can confer well-documented economic advantages to firms (Khan, Lewis, & Singh, 2009). In particular, the issues of identifying and leveraging the potentially significant differences across customers in terms of lifetime value have been fundamental for customer relationship management over the last two decades (Rust, Lemon, & Zeithaml, 2004). Moreover, the idea of “customer-centricity” demands the identification of a customer minority who should enjoy more attention from marketers as compared to other customers (Fader, 2012).

AI systems' emergence is not expected to overthrow relationship marketing, but instead will render it more accurate, discriminating, and scalable. This may have a substantial effect on the fundamental nature of customer-firm relationships in multiple domains and may increase customer equity. It may have implications not only for differentiation among customers but also among firms, some of which will find competing for customers a more significant challenge over time. We argue that marketing researchers and thought leaders must gain a better understanding of AI-CRM's potential implications when contemplating how firm-customer relationships will evolve.

Our paper follows the process depicted in Fig. 1. We first discuss two critical capabilities enabled by AI: the ability to leverage big customer data and the ability to communicate, understand, and create the way humans do. Then we move to its effects on the tasks of customer relationship management:

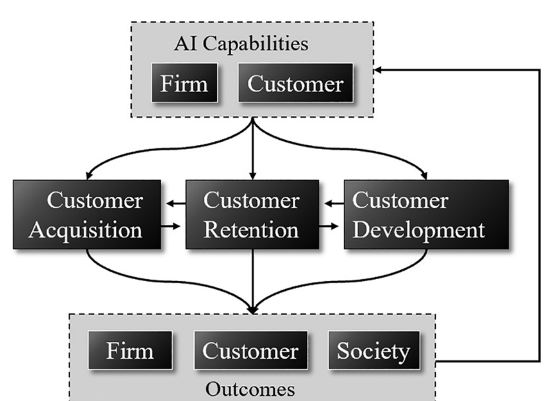

Fig. 1. The AI-CRM effect.

customer acquisition, development, and retention. We conclude by focusing on AI-CRM's potential outcomes for consumers, firms, and society in general.

We note that our focus is not prescriptive. We believe that in this stage we need to highlight the issues that arise and the problems that emerge as AI changes the ability to manage customers, and in particular to differentiate among them. A normative piece on what to do will require a separate effort. However, we do consider the matter toward the end of the paper when we discuss the role of regulators. One issue is that "doing it right" may differ depending on which perspective (firms or consumers) is weighted more heavily. It may be that similar to the case of privacy; regulators may have to intervene to make things "right" when the balance of power changes.

Capabilities

We have recently witnessed an increase in what software can do, imbued as it is with sufficient capabilities to justify the term intelligence, as defined above. We are now nearly inured to computer vision; advanced, if imperfect, robot and automotive mobility; speech recognition; real-time language translation; and victories over our human brethren in chess, go, no-limit Texas Hold'em poker and even the video game StarCraft II. Nor is there any sign that the AI capabilities trend line is diminishing. As such, it is now time to ask how such capabilities will be applied to CRM.

When we refer to AI-CRM capabilities, we mean those AI capabilities useful for the interrelated CRM tasks of customer acquisition, customer retention, and customer development. Given that, we will discuss two AI-CRM capabilities: (i) leveraging big customer data, and (ii) communicating, understanding, and creating the way humans do. We believe that the prevalence of machine learning techniques in CRM has already made the potential of AI-CRM abundantly clear. Machine learning has been used to enhance relationship-acquisition advertising campaigns (Schwartz, Bradlow, & Fader, 2017) to create superior recommendations to develop existing relationships (Overgoor, Chica, Rand, & Weishampel, 2019) and to detect churn sooner to enhance relationship retention (Ascarza, 2018). Also, using human-like chatbots for communication became a well-established method for dealing with service failure and hence churn avoidance (De Keyser, Arne, Alkire, Verbeeck, & Kandampully, 2019). These precursor examples highlight the potential for AI-CRM to leverage vast amounts of data in predicting what ads customers will click on, what products customers will like, or which customers will churn.

Leverage Big Customer Data

The Internet of Things, and related quantification and digitalization trends, lead to the obvious expectation that we will see much larger CRM datasets used by firms in the future than are used currently. Data, therefore, are increasingly a foundation for value creation and extraction. We illustrate this principle with two historical anecdotes. In 2009, Google bought the telecom company GrandCentral and rebranded it Google Voice. Among other strategic advantages, this gave Google access to an ever-growing corpus of voice messages. Google software specialists used the corpus to learn how to produce voicemail transcripts (Beaufays, 2015) and thereby gain experience with spoken speech. This capability would eventually be used in the AI behind Google's voice-activated assistant. Along the same lines, Amazon picked books as its first product category. In addition to the wide assortment of books in the market place, we believe that the choice also allowed Amazon to attract the right (i.e., more affluent, and thus more valuable) customers and leverage their browsing and transaction data to refine their future growth into other product categories. In both cases, we witnessed a unique historic opportunity to create an imperfectly imitable resource (Barney, 1991).

Of the three Big Data Vs (volume, variety, and velocity), we believe variety is the strongest driver of competitive advantage. In the context of AI-CRM, variety refers to the breadth and the scope of the customer database. Already, companies have house lists with thousands of data fields (Deighton, 2019). Importantly, a firm will need to be perceived as trustworthy to achieve Big Data variety through establishing multiple partnerships with external entities, thereby rendering trust (Bart, Shankar, Sultan, & Urban, 2005; Urban, Sultan, & Qualls, 2000). Even more important, every time a firm seeks to capture a new type of data, there is an opportunity for the external entity that provides that data to rethink the value exchange. While increasing variety is more challenging than increasing volume, we suspect that once the volume is sufficient for separating training, test, and validation data, expanding the scope of customer data yields a proportionately stronger impact on firm performance: The more data types there are, the more opportunities there are for discovering associations therein.

In summary, acquiring and maintaining more diverse data sets will be a significant source of AI-CRM competitive advantage. Interestingly enough, a firm will need to be perceived as trustworthy to achieve Big Data variety through establishing multiple partnerships with external entities, thereby rendering trust even more critical (Bart et al., 2005; Urban et al., 2000); every time a firm seeks to capture a new type of data, there is an opportunity for the external entity providing that data to rethink the value exchange.

Communicate, Understand, and Create the Way Humans Do

Long before our current AI era, Alan Turing suggested that one could assess AI by checking if it could fool humans into believing that they were communicating with other humans (Turing, 1950). With the growth of service chatbots, Twitter bots, and voice-activated digital assistants, it is increasingly evident that software is getting better at communicating like a human. For example, Precire is a German company whose software listens to recordings of recruitment interviews. This allows firms to do an initial screening of candidates, eliminating those whose speech rate, speech volume, number of filler sounds, sentence complexity, and word choice that can predict failure at the job (Morrison, 2017). Communications capabilities of bots and automated assistants now allow for near-human customer contact at only a modest marginal cost per contact.

AI appears to be moving along a trajectory that began at mechanical capabilities, passed through analytical capabilities and intuition, and has nearly arrived at empathic capabilities, necessary to recognize and understand human emotions (Huang & Rust, 2018). We have already seen that algorithms can score one's personality better than friends, or even than oneself (Youyou, Kosinski, & Stillwell, 2015). Indeed, not only computer scientists can improve AI, but neuroscientists also work on AI, as understanding how both computers and humans learn can inform algorithm design.

In fact, AI-CRM capabilities do not need to achieve full human empathy to complement or even replace human CRM judgment. Consider employees of advertising agencies as an illustration. Whether these are the mass-market advertising specialists who come up with ad execution, high-performance sales personnel who close the deal, or direct marketing copywriters whose words jump off the screen, the ability to tell a brand's story or write compelling copy has thus far been restricted to humans. There is reason to believe that this human monopoly on creative marketing capabilities has ended or will shortly end. Recently, a computer-generated work of art sold for $432,000 (for a review of AI in art and related topics, see Bailey, 2018), and ad agencies already experiment with offering clients AI-produced ads that perform better than human-made ones (O'Reilly, 2017).

An approach known as *generative adversarial networks* is one example of an algorithmic approach to creative AI (Goodfellow et al., 2014). In the technique, two opposing neural networks compete against each other. One network, called the *discriminator*, is trained to categorize input examples (like art) as genuine or fabricated, producing a number close to or equal to 0 if the discriminator predicts that the input is fabricated, and close to or equal to 1 if the prediction is that the creative input is genuine. The other neural network, called the *generator*, fabricates art, feeds it to the discriminator along with real examples, and receives feedback (as mentioned, in the interval [0,1]) on how well it fooled that network. As the discriminator gets better at categorizing genuine creative work vs. the poseur's fabricated generator output, the generator gets better at creating the material that can fool the discriminator. We see no reason that such generative adversarial networks cannot be applied to executing creative CRM tasks. One near-future implementation will be making chatbots appear more human in service interactions (Luo, Tong, Fang, & Qu, 2019).

We expect that the AI-CRM capabilities described above will not be easy to acquire. Competition will likely be fierce for those with the knowledge and skills to utilize AI-CRM. As location and proximity matter in the transmission of knowledge (Audretsch & Feldman, 1996), it is likely that the expertise required to train and utilize AI-CRM will concentrate within a small number of geographically proximate technology due to hubs' ability to facilitate information flow and knowledge transfer between firms (Ketchen, Snow, & Hoover, 2004). The importance of regional clusters may be mitigated by the global growth in business analytics programs.

If the implementation of pre-AI CRM technology in a customer relationship context is any indication (Bohling et al., 2006), building out AI-CRM might not always go smoothly. In general, managing value creation has shifted away from managing people and things toward managing software assets like AI-CRM (Hofacker, 2019). It remains unclear how well marketers will handle this shift. Rendering AI-CRM implementation all the more daunting is the fact that AI-CRM capabilities may not reside within a single CRM system: Firms generally supplement CRM packages like SugarCRM, Salesforce CRM, or SAP CRM with a campaign management system for customer selection and targeting; and with an ERP system for tracking costs. AI-CRM requires combining different data sources stored in various applications that are often not (well) integrated.

To summarize, we believe that AI-CRM will move toward improved leveraging of big customer data, and communicating, understanding, and creating the way humans do. As we will outline next, we are skeptical that all of this will lead to a value exchange utopia for both firms and customers. Let us see how this plays out in the next section, as we consider the impact on firms' abilities to acquire, develop, and retain customers and the consequent outcomes.

Customer Relationships

Acquisition

We proceed by outlining AI-CRM's potential to improve acquisition efforts. Given that CRM, in general, aims to increase a firm's customer equity, we discuss its potential incremental effects on: (1) CLV of new customers, (2) customer acquisition costs, and (3) number of new customers.

Generally, firms rely on internal data to select prospects (Cao & Gruca, 2005). A recent study by Tillmanns, Ter Hofstede, Krafft, and Goetz (2017) proposed a machine-learning algorithm to select targets for customer acquisition using data from an external vendor with personal, household, and neighborhood information. While these data are already valuable, we expect tighter integration of external data sources with individual buying behavior and interests, and broader availability at large scale with increased variety and scope. Such data will feed algorithms to further improve the selection of prospects, leading to more data, and therefore creating a positive feedback loop. In sum, AI-CRM will enhance a firm's ability to predict prospects' CLV and to use this information in managing the customer acquisition process through *selective acquisition*, whereby only more profitable ("better") customers will be acquired. Furthermore, we expect AI-CRM to generate more detailed insights into the quality of acquired customers by considering the path by which the customer is acquired; that is, gaining knowledge about decision journeys of current customers (Batra & Keller, 2016) enables optimizing acquisition path not only in terms of the number of newly acquired customers but also concerning their quality (i.e., CLV) (Verhoef & Donkers, 2005).

Moreover, more precise and highly effective targeting will increase the customer conversion rate, thereby reducing customer acquisition costs. Currently, most studies pay little attention to the scope of external data but improvements in data management capabilities will enable firms not only to better identify high-CLV prospects but also to develop offerings that meet these prospects' needs.

Rich data on individual consumers gathered through variety of available tracking technologies (i.e., variety of data) will provide a holistic view of prospects. Firms will gain insights into prospects' pain points and the gains they are seeking. With the support of AI-CRM, firms will be able to formulate value propositions that address high-CLV prospects' needs. Firms already use morphing tools (Urban, Liberali, MacDonald, Bordley, & Hauser, 2013) to adjust online and messaging content according to prospects' needs aided. One example is the start-up Brytes, that renders consumers' digital body language visible and uses this information to identify the psychographic traits of every user of a given website in real-time and deliver the information and assistance that a consumer needs. Such developments will decrease customer acquisition costs in general, and will also affect new customers' CLV positively.

Another possible benefit of predictive AI is the ability to anticipate larger trends and movements, and thereby help formulate value propositions therearound. Recently, several studies using text-mining approaches have demonstrated that colossal quantities of external data like user-generated content (UGC) deliver quick and valuable insights. For example, Decker and Trusov (2010) formulated an approach to estimate aggregate consumer preferences from UGC; Netzer, Feldman, Goldenberg, and Fresko (2012) illustrated how UGC provides an understanding of market structures and competitive landscapes; and Gensler, Völckner, Egger, Fischbach, and Schoder (2015) showed how listening to a firm's customers delivers insights into a brand's image. While in the past such studies often used lexicon-based algorithms to mine UGC, AI-flavored machine learning algorithms such as support vector machines (SVM), random forests (RF), or natural language processing (NLP) are gaining popularity and are improving marketers' ability to extract valuable insights from external text-based data (e.g., Hartmann, Huppertz, Schamp, & Heitmann, 2019; Toubia, Iyengar, Bunnell, & Lemaire, 2019). While research on the (automated) identification of trends based on external data is currently scarce, knowledge about trends can generate a competitive advantage by creating superior value. Google Trends, for instance, has proved to be a valuable aid for firms to identify trends. For example, Du, Hu, and Damangir (2015) examined the potential of using trends in online searches for feature-related keywords as indicators of trends in the relative importance of the corresponding product features. They showed that augmenting marketing-mix data with feature search data in a market response model substantially improves such models' fit. Such developments will also facilitate the acquisition of new customers.

Beyond the scope of learning about prospects and trends, AI could also help firms to gather information about competitors in existing markets. For example, it could determine who is a customer of which firm and enable companies to target high CLV customers of specific competitors with personalized offerings. Furthermore, AI tools can leverage UGC to identify dissatisfied customers of competitors and to proactively address them with counteroffers. Beyond wooing away high-value competitors' customers, firms could also utilize AI to learn about their competitors' strategies by observing which customers are being targeted. In summary, AI-CRM that utilizes and combines internal and external data opens up new possibilities in the customer acquisition process, helping firms to grow their customer equity.

Development and Retention

Following customer acquisition, two aspects of customer relationship management are key to the creation of customer profitability: *Customer development* refers to efforts to increase per-period profit from current customers such as increasing margin, frequency, cross-selling, or upselling. *Customer retention* relates to efforts to increase the *duration* of the customer–firm relationship. These two processes can be interrelated (Gupta & Lehmann, 2005), and we will discuss possible shifts in light of several developments that we anticipate in markets where AI-CRM systems are deployed. Many AI capabilities enhancing value to the customer that were discussed in the context of customer acquisition are also relevant to development and retention. However, this section focuses on the major issues particularly notable for development and retention: *personalization*, *habit formation*, and the effect of *social networks.*

Personalization

Following our view of *AI-CRM* systems as those exhibiting sufficiently flexible adaptation, notable use of such systems is to enable firms to create a more personalized dialogue with customers that takes into account the former's purchasing history and interactions, and adapt the resulting marketing mix elements to the individual customer (Kumar et al., 2019). While AI systems mostly perform mechanical and analytical tasks today, they will gradually move to perform communication tasks that demand the imitation of human intuition and empathy (Huang & Rust, 2018). This will, in turn, enable an interactive ability to predict individual customer needs and potentially satisfy them. A straightforward implication thereof is that we can expect greater success in developing customers and retaining them. Thus, customers' lifetime values should increase, and likewise the motivation to invest in customer acquisition.

A second implication is that firms can decide who NOT to invest in. While currently, many efforts to develop and retain customers are geared toward the customer population in general, managers are still encouraged to focus only on those customers who will create strategic advantage (Fader, 2012), and AI-CRM-driven personalization will enable firms to increasingly move in this direction. Thus, we expect to see increasing use of *selective development and retention* that focus only on a subset—sometimes a small one—of customers. Indeed, across a variety of markets such as communications, apparel, cars, travel, and credit cards, the decision to invest and effort to retain (e.g., by better service and perks) is based on customers' expected lifetime value (Safdar, 2018). Given differences in expected customer profitability, marketers are also advised to be selective about which customers they aim to reactivate (Kumar et al., 2015). Similar considerations apply for the decisions on whether to develop a customer, in particular since some customers are not profitable to begin with (Shah, Kumar, Qu, & Chen, 2012). Thus, consultancies advise firms to focus on their cross-selling campaigns on high-value customers (Senior, Springer, & Sherer, 2016). We will further expand upon selective development when we consider the outcome for customers later.

Habit formation

Considering the role of technology in retention and development raises the need to discuss what has emerged in recent years as a fundamental issue in our understanding of why customers continue to do what they do, or *habit formation* (Duhigg, 2012; Shah, Kumar, & Kim, 2014). New technologies play a unique role in creating habit (Eyal, 2014), and thus AI is likely to play a role in how habits affect (or not) consumer decision-making.

Increasingly managers are encouraged to adjust their thinking by focusing on customer habits instead of customer loyalty as the driver of market success (Lafley & Martin, 2017). That view is consistent with an increasing emphasis in the business and academic literature on habits as critical drivers of customer behavior (Duhigg, 2012; Eyal, 2014; Wood & Rünger, 2016). Habit-forming behavior is, by definition, governed by automaticity. It requires minimal cognitive attention and is strongly related to the frequency of previous behavior occurring in a stable and recurring context (Shah et al., 2014). Beyond simple repeat purchases, habits may drive decision-making in various other stages of the customer journey such as response to promotions, returning products, and making dedicated shopping trips (Shah et al., 2014).

One might wonder whether the AI revolution is not antithetical to that of habit-forming behavior, because as decisions become less complex, less AI-based intervention will be needed. We contend, however, that AI will make habit-forming behavior more widespread, and help firms to manage their customer relationships via habits.

AI-CRM's ability to encourage consumer automaticity can be complemented with the ability to track habit-forming behavior and other aspects of the consumers' environment. Using Internet of Things (IoT) data inputs, various sensors around the consumer can collect and analyze information on the status of products, stockouts, and the need for refills. Easy transmission mechanisms such as Amazon's Alexa enable customers to order products nearly effortlessly. Machine learning algorithms can be used to identify needs promptly and offer customers a reasonable alternative right away. As algorithms do a better job of providing the right product at the right time, consumers' trust therein will increase, as well as their willingness to skip the search process and rely on the firm.

This development, in turn, builds up a cumulative advantage over time: the more one uses the firm, the more one is used to it and the habits associated with it, the higher the likelihood that one will continue to purchase therefrom (Lafley & Martin, 2017). Also, the more data are gathered, the better the firm can learn the individual's needs and preferences, and further use this information to strengthen the habit.

With better-tailored solutions, customers of direct-to-consumer businesses will be less likely to shop for alternatives. As buyers increasingly trust the seller, and as data become more available, firms can further enhance current algorithms' abilities to get the right product to the right customer at the right time (Li, Sun, & Montgomery, 2011). Consequently, we expect the AI-CRM-led "habit economy" to improve firms' ability to cultivate their customers. AI-CRM systems will help to prevent cross-selling to non-profitable customers and increase the motivation for profitable cross-selling activities (Shah et al., 2012).

In terms of retention, once a habit-forming relationship starts, customers put less effort into renewed decision-making, as the latter creates de facto switching costs for the customer. Via past behavior and the information that they have provided in the past, customers have enabled their service provider to learn their tastes and wants. Moving to a new provider would demand new learning, and the better the job current providers do, the higher the switching costs. To the extent that AI-CRM improves CRM, switching costs will increase. Given that even low switching costs can create a lock-in effect with customers (Blut, Frennea, Mittal, & Mothersbaugh, 2015; Zauberman, 2003), we expect AI-CRM leaders to improve their retention of desirable customers.

Note, though, that AI systems may not only increase switching costs for current customers, but new firms may be able to use the AI-driven learning process to reduce switching costs to them and so attract customers, as we also discuss in the *Acquisition* section. The question is then which force will be stronger, retention or acquisition? AI capabilities depend heavily upon the use of large volume and variety of customer data to learn and adapt, and these data are much more likely to be available for current rather than potential customers. Thus, we expect that overall, AI-CRM effect on increasing switching costs for current customers will be higher than its effect on lowering switching costs by competitors.

Agents and habit formation. AI enabled the rising popularity of smart assistants such as Alexa, Siri, or Bixby that help individuals in their everyday activities, many of which are consumption-related. As AI-CRM systems develop and smart assistants gain more access to product data and consumer input on a wide range of products, habits, and practices, they may become much better in identifying products and solutions that meet customer needs.

This contributes to the process of habit formation: The more the smart assistants learn how to anticipate and understand user needs, the more customers will get into the habit of trusting them to make decisions, with the implications for development and retention discussed above. However, the assistants operate at the platform level, not at the individual brand level, and thus platform-enabled brand choice by customers may be affected by the economic interests of the platform. Further, platforms may restrict brand access to customer data, to preserve the advantage in understanding customer needs. This would mean that for consumers who buy directly from the brand, personalization and habit formation may help to create higher brand-specific customer lifetime value. For consumers buying through assistants, lifetime value depends on the assistant's actions. In other words, the assistant's interests and preferences will mediate the brand-related lifetime value created in this case.

The ability of agents to affect habit formation raises an important point that should be emphasized. AI can be used not only to build on and sustain existing customer habits but also to learn how to form new or break old habits. AI systems can leverage customers' responses to past interventions for stimulating habit formation. More generally, using AI-CRM to optimize timing, frequency and intensity of firm interventions can create and strengthen customer habits much more effectively than marketers do this today.

Role of Social Networks

Emerging research points to the role of social influence in customer development and retention. Due to the expected homophily in purchase patterns among social network members (Haenlein & Libai, 2013), information on members of the social network and their consumption can serve as valuable input into the choices of which products are optimal candidates for the development of focal customers. Given the evidence on customer churn's social impact (Haenlein, 2013; Nitzan & Libai, 2011), the social network information can become an integral part of churn prediction and management.

Despite of the established importance of social networks' role in customer decision-making and profitability (Lamberton & Stephen, 2016; Muller & Peres, 2019), most marketers are still not taking advantage of customer connectivity information given the difficulties in the identification and analysis of customer networks for specific products. Due to the complexity of the analysis, much of the investigation to date had been restricted to using data on relatively small social networks. AI applications will allow such investigations to expand and deepen, enabling a much better leveraging of customer network data. Advanced machine-learning tools allow for the identification of social networks and of particular communities within the networks using a variety of online data (Guerrero, Montoya, Baños, Alcayde, & Gil, 2017; Perozzi, Al-Rfou, & Skiena, 2014). Driven by smartphone ubiquity, location-based data can further enhance the ability to identify customer social networks using advanced machine learning techniques to analyze these large-scale data (Eagle, Pentland, & Lazer, 2009). This network data can then be used to better personalize the interaction with customers (Chung, Wedel, & Rust, 2016).

The use of social network information has implications for all three aspects of customer management: acquisition, development, and retention. The role of social network analysis in optimizing customer acquisition, in particular in the context of new product growth, has been much cited in the marketing literature (Muller & Peres, 2019; Nitzan & Libai, 2011). Yet, since large-scale data on customers and their social interactions are more available for current customers than for potential ones, we believe that the use of AI to conduct social network analysis will have higher impact on customer development and retention. This will be particularly relevant to products such as digital games, where customers' social network activities are routinely collected (Liu, Liao, Chen, & Chiu, 2019).

Outcomes

Customer-Related Outcomes

Given AI's aforementioned abilities, we consider outcomes for customers, firms, and markets in general, starting with customers. Indeed, many customers may enjoy enhanced personal service, the benefit likely to become less costly as technology enables firms to replace humans in an increasing number of service jobs. However, as follows from the previous discussion on selective acquisition, development, and retention, AI-CRM is not likely to deliver such benefits equally to all consumers. We next elaborate on the reasons therefor.

Customer Prioritization

Historically, as customer databases began to provide indications of concentration in customer profitability (Zeithaml, Rust, & Lemon, 2001), firms moved toward *customer prioritization* under which customers are treated differently based on expected profitability (Homburg, Droll, & Totzek, 2008). Overall, customer prioritization is viewed as a useful tool for managing customers (Rust, Kumar, & Venkatesan, 2011). Indeed, evidence from multiple industries suggests that service levels are related to customers' expected profitability (Daily Kos, 2016; Safdar, 2018) and that the differences may have widened in recent years (Schwartz, 2016). Differing treatment can apply to any part of the marketing mix, including the level of service, price, and promotion; it can even lead to customer abandonment (Haenlein & Kaplan, 2012).

It is commonly assumed that better CLV prediction by AI-CRM would allow for greater discrimination across the CLV distribution. Since the customer profitability distribution often resembles a Pareto more than a Normal (Fader & Toms, 2018), AI-CRM's predictive ability will motivate firms to focus their efforts and investments on a relatively small segment of the CLV distribution. The same CLV distribution may therefore further increase disparity (O'Neill, 2016; Wertenbroch, 2019).

As data collection and mining techniques have improved, marketers have gained the ability to identify and track individual customers (Andrews, Goehring, Hui, Pancras, & Thornswood, 2016; Ngai, Xiu, & Chau, 2009). Still, up until now, marketers have been restricted in their ability to apply customer prioritization at scale due to limitations on available information on individuals and capabilities required to reliably integrate and analyze information from multiple sources in real-time. For example, consumer spending volatility has been shown to restrict firms' ability to predict customer lifetime value (Rust et al., 2011).

AI-CRM systems will incrementally allow marketers to overcome such issues. AI-CRM will enable rapid response personalization that stems from the improved identification of customers (Roberts, 2019), faster and more precise updates of future profitability using machine learning (Martínez, Schmuck, Pereverzyev Jr, Pirker, & Haltmeier, 2018), and, more generally, the ability to obtain individual-level information from the traces that consumers leave on their journeys (Padilla, Ascarza, & Netzer, 2019). It will enable rapid, time-sensitive decisions to invest in the right customer acquisition and the practice of selective development and retention. For some consumers, this will mean higher incentives to become firm customers at the acquisition stage, better goods and services at the development stage, and possibly even getting lower prices motivated by the retention consideration. Other consumers will be selectively under-acquired, under-developed, and under-retained.

Since by definition only a minority of customers can be prioritized, overall satisfaction of the customer base can decrease (Gerstner & Libai, 2006). Further, customer prioritization affects customer entitlement and word of mouth (Wetzel, Hammerschmidt, & Zablah, 2014). There can be also legal implications where minorities or other segments are discriminated against (Ukanwa & Rust, 2018). This does not imply, however, that customers will not be served: For some less profitable customers, new businesses will emerge whose offerings will match their ability and willingness to pay (Rosenblum, Tomlinson, & Scott, 2003). For many, it will simply mean different levels of the marketing mix. Yet generally and for many consumers, this will mean a substantial reduction in the quality of products and possibly higher prices, of which they may not be even aware: Due to the ability to target individuals and the aforementioned habit formation process, prioritization will not necessarily be noticed.

This targeting ability is not restricted to the purchase process but can be implemented in all aspects of the customer relationship spectrum. For example, recent research in the legal literature warns against sellers' ability to use big data and predictive analytics to identify frequently complaining customers and avoid selling to or disarming them before they can draw attention to sellers' misconduct (Arbel & Shapira, 2020).

Income Inequality and Prioritization

The considerable increase in income disparity in various parts of the world in the last three decades (Piketty & Saez, 2014) naturally leads to increased differences in consumption (Aguiar & Bils, 2015), creating additional skewness in CLV distributions. In a general sense, customer prioritization increases disparity in the population and prods the drift toward a more polarized society wherein some customers will get better and possibly lower-priced products than others. For example, machine learning techniques that have been used on mortgage data of millions of borrows allow for more accurate pricing of default risk and thus for a greater supply of credit. However, the benefits in cheaper mortgages go disproportionately to the more affluent borrowers (Fuster, Goldsmith-Pinkham, Ramadorai, & Walther, 2018). Recent research has demonstrated that such techniques can even help to identify defaulting borrowers by the text they write when asking for the loan (Netzer, Lemaire, & Herzenstein, 2019).

Overall, differential treatment of less affluent consumers will raise difficult moral and political questions about impact of AI-CRM systems on an increasingly polarized society.

Role of Consumer Technology Skills

It has long been established that disadvantaged consumers may pay more than higher-income customers due to the former's limited scope of purchases and the ability to take advantage of market opportunities (Goldman, 1976). One might imagine that AI systems can help such consumers in this regard. They may use AI-based smart assistants that capture and analyze their preferences to help them face increasingly complex marketplaces. In that sense, some bottom-of-the-pyramid customers who are traditionally less able to take advantage of value-based market opportunities can use such assistants to get better value for a lower price.

The question of skills and AI's effect may be task-dependent. For simpler tasks such as finding a product to purchase in a certain category, an AI-based device such as Alexa can help less-skilled individuals to navigate the marketplace with the help of technology. However, for more complicated tasks (such as finding the optimal product, overcoming marketers' attempts to draw the customer in a certain direction) the efficient use of AI may depend on skills that may start even with the knowledge of which software and technology to use (Agrawal et al., 2018; Wilson, Daugherty, & Bianzino, 2017). Taking advantage of increasingly sophisticated assistants will demand skills that are not necessarily available to large segments of the population. Given that, even consumer-side AI may increase disparity among customers.

Consider the case of Alexa and Echo smart speakers. Together they enable customers to order products seamlessly and at a rather affordable cost, providing the possible basis for a smarter household shopping environment. Yet, the market opportunity draws more higher-income users than others (Kinsella, 2018). One of the reasons for this is that even this seemingly simple IoT environment demands some technical know-how (e.g., setting up a household profile) that may create obstacles for disadvantaged population segments.

Transition Period

While AI may eventually create a flawless service environment, the transition between classic CRM and AI-CRM will not be flawless. For example, while chatbots may be more cost-effective than human employees, the service experience that they provide can be subpar in the earlier stage, generating consumer frustration (Kannan, 2019). As with other self-service systems, factors such as age, gender, and socio-economic status will likely affect users' technological savvy, and likewise their aptness, or resistance, to the new technology (Blut, Wang, & Schoefer, 2016; Venkatesh, Thong, & Xu, 2012). Furthermore, it has been found that older and lower-income individuals may adopt innovations later and tend to perceive innovations as less useful (Arts, Frambach, & Bijmolt, 2011; Laukkanen, 2016). This will affect how fast the disadvantaged consumers will adopt and start using AI-driven tools. At this transition time, highly skilled individuals find it less challenging to use service systems partly driven by AI, whereas the technologically disadvantaged will find it hard to benefit therefrom.

Firm-Related Outcomes

As discussed above, AI-CRM is a highly resource-dependent activity for companies to engage in. Consistent with the resource-based view (Barney, 1991), this implies that firms with superior resources will gain a competitive advantage that can, in turn, lead to monopolies or oligopolies. Note that in the context of AI, necessary resources include, among others, big data, properly skilled staff, management agility, and superior computing power, as well as proprietary use of top-performing algorithms.

There are some cases wherein smaller startups can use their agility and technical orientation to take advantage of the promises AI offers in the context of customer relationships. However, we believe that in most cases, larger firms have the potential to benefit more due to their access to resources. Among the essential resources that larger firms possess, two are notable. One is access to large databases that will enable the machine learning to train and increase effectiveness. The second is the access to trained professionals that will manage the process, which is especially important in light of the AI skills crisis (Marr, 2018), where the demand for AI professionals is much larger than the possible supply. Large companies have a much better ability to invest in recruitment, compensation, and organizing AI professionals in large enough departments that will enable the creation of effective knowledge centers in the organization.

While most AI-CRM benefits derived by firms relate to an improved value proposition, AI-CRM also often reduces the cost of serving consumers, as the emerging technologies in many industries allow substitution of human labor with cheaper machines and automated decision making to optimize interactions with consumers at various points on their journeys. As aforementioned, the more data's scope and variety increases, the more the firm can learn individuals' needs and preferences. Such acquired knowledge can then be leveraged into offering better value propositions to these individuals not only in the product category where the data were collected but also in other product categories.

Consequently, as AI-CRM enables companies to derive more value (on average) from consumer acquisition by leveraging customer data across multiple product categories, we expect the competition among firms at the acquisition stage to intensify. Further, we expect to see more mergers and acquisitions that focus on the value of merging (or acquiring) consumer data, compared with other firm capabilities. Finally, the increased importance of fast, direct access to consumer data may generate a higher sustainable competitive advantage for direct-to-consumer brands competing with traditional retail brands.

Given the increasingly more granular nature of consumer data becoming available, such competition will be focused not on a consumer segment level, as it traditionally has been, but instead, firms will be competing for each consumer. Further, given the improved prediction of customer lifetime value, we should expect such competition to be uneven across consumers. For consumers with high expected lifetime value, the competition will intensify, resulting in such consumers deriving higher value (e.g., airlines tend to offer more value to current and potential customers who are expected to fly often). On the other hand, the competition will become less intense for consumers with lower expected lifetime value, resulting in a lower value for them. It is possible, however, that such increased discrimination in provided value may be mitigated in industries where delivering horizontal differentiation is easier, such as apparel.

Regulation

Rise of market concentration usually associated with regulators intervening and breaking up existing structures. Yet recent examples, such as the US aviation market, have shown that this is not necessarily the case, at least for a certain transition period (The Economist, 2018). For the case of AI, the problem is particularly pressing, as the traditional argument of protecting consumers against price gauging resulting from monopolies often cannot be invoked, as many companies in this sphere provide their services free of charge (e.g., Google, Facebook). For those services that are not free, the competitive advantage of superior resources may enable monopolists to offer higher value to customers due to a combination of providing superior value (e.g., due to network effects) at a lower cost (e.g., due to economies of scale, fewer marketing expenditures).

As lower costs make applying anti-trust regulation quite challenging, firms may fully take advantage of their market power, which will raise concerns on the parts of regulators. The question, however, is whether, at that stage, regulation will even be possible. Moreover, in countries where companies are allowed to invest some of their profits in lobbying (e.g., such as the United States), imposing regulation may be associated with significant political risks.

It is also possible that AI may create a system that self-regulates. The same AI systems that help firms provide superior product offers can help customers identify the companies most adapted to their needs. We may witness the rise of third-party providers enabling high-value customers, or customers with superior data profiles, to find the perfect companies with which to interact. This would function in much the same way as recommendation sites do today. The danger, however, is the selective discrimination we have discussed above – customers who are considered unprofitable or barely profitable will be abandoned by most firms (Haenlein & Kaplan, 2009). This, in turn, may lead to the rise of new competitors specializing in this type of client base (Rosenblum et al., 2003), as well as more intense competition among firms who abandoned them (Subramanian, Raju, & Zhang, 2014). Also, receiving consistently lower service may push such lower-value customers to falsify their online data and generate fake online profiles. Such information is inherently difficult to spot, as the recent discussion around fake news indicates.

What all of this implies is that smart customers will leverage AI's power to become more strategic themselves (Haenlein, 2017; Lewis, 2005). Customers will learn how to better negotiate with firms, use their personal data as a strategic advantage, and generally shift value capture away from firms. Automatic and AI-enabled solutions will emerge to support customers in those activities. As we discussed, AI will allow firms to better discriminate among customers and to avoid providing superior customer service or better products to customers who do not "deserve" this treatment. Yet the same AI may help some customers to identify the decision rules used by firms in providing such service and leverage those rules to their advantage. This counter-strategizing may widen the chasm between high-value and lower-value customers as differences between customers will stem not only from the increased ability of certain firms to discriminate but also from the increased ability of certain (most likely higher-value) customers to navigate firms' strategies to their advantage.

In such a world, CRM would become a constant race between firms trying to predict customer behavior, alongside a segment of customers trying to anticipate or reverse-engineer firms' decision rules. At the same time, a large number of customers may become more and more frustrated by the nature of the firms' marketing mix decisions that drive increasing consumer disparity, therefore increasing pressure on regulators to take action to mitigate it. Governments already recognized some of the problems that big data and the ability to analyze it create in this regard (e.g., White House, 2015).

Ultimately, intervention by regulators may be needed to balance the resource-driven concentration of firms with the emergence of falsified data and strategic customer behavior. Such a need will become more pronounced as more companies start discriminating against relatively low-value customers. Examples of such interventions can range from regulating the use of automated solutions (e.g., in France, some self-service solutions are only allowed to operate during usual business hours, and not 24/7), to disproportionally taxing AI-enabled value creation (to compensate for the advantage such systems extend compared to hiring human personnel), to the dismantling of monopolies (e.g., as suggested by the #BreakUpBigTech movement).

Yet regulating AI may not be that easy (Scherer, 2016). AI is difficult to regulate because of the definitional, ex-post, as well as ex-ante problem. First, we need a clear and legally binding definition of the object to be regulated. This does not yet exist in the case of AI. Second, there are several regulatory problems at the ex-ante stage (R&D of the targeted AI system) as well as the ex-post stage (whenever AI is put on the market) (Scherer, 2016).

What amplifies complexity even further are the different systems of thoughts about regulation. While the US is relatively reluctant to regulate, Europe has been making more use of its regulatory powers lately (Kaplan & Haenlein, 2020). In China, the government and state-affiliated entities are leading AI development and application of AI-CRM systems in multiple domains, which creates another set of challenges and considerations. Cultural dimensions also must be considered: European legislation is less tolerant of asking customers to share data, while the US and especially China, have fewer restrictions thereon.

This highly complex interplay may explain why some in the corporate world are advocating for more regulation. Companies such as Facebook are calling for government intervention (e.g., Anderson, 2019) and Microsoft's president Brad Smith recently called for "thoughtful government regulation" of technological advances in facial recognition. Elon Musk stated early on, "I'm increasingly inclined to think there should be some regulatory oversight, maybe at the national and international level" (Gibbs, 2014).

Conclusion

One could argue that much of AI's contribution to how firms will manage their customer relationships can be considered simple enhancements of technology-enabled processes that have been unfolding for some time. Indeed, an information-intensive world in which customers are managed individually, and their demand is well predicted, has been envisioned for decades (Blattberg et al., 1994). However, until AI methods began emerging, the pace of progress was moderate, and much of this futuristic vision has not yet materialized. As this future vision is rapidly becoming our new reality, we argue that marketers should not only focus on how new methods of customer interactions are conducted but also their overall consequences for the fundamental ways that firms build "relationships" with customers.

The implications thereof are not trivial: We are moving toward an economic system wherein customer prioritization may dominate much of customer relationships, and where only a minority of customers is capable of taking advantage of the new technologies. While in some cases marketers will find that customer discrimination is not always optimal from an economic standpoint (Ukanwa & Rust, 2018), this will not necessarily represent the majority of cases. We expect that there will be groups of individuals that may be affected by this prioritization wherever they consume. Hence, AI-CRM systems may become a concern and a consideration of both regulators and human rights groups (World Economic Forum, 2018). Marketing academics' experience and knowledge of this matter give them a particular responsibility to be an active voice that follows AI-CRM systems' development, identifies the concerns, and makes recommendations on how to address the new environment of customer relationships that we all face.

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There are no conflicts of interest to declare.

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