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RESHAPING THE CONTEXTS OF ONLINE CUSTOMER ENGAGEMENT BEHAVIOR VIA ARTIFICIAL INTELLIGENCE: A CONCEPTUAL FRAMEWORK

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ABSTRACT

As new applications of artificial intelligence continue to emerge, there is an increasing interest to explore how this type of technology can improve automated service interactions between the firm and its customers. This paper aims to develop a conceptual framework that details how firms and customers can enhance the outcomes of firm-solicited and firm-unsolicited online customer engagement behaviors through the use of information processing systems enabled by artificial intelligence. By building on the metaphor of artificial intelligence systems as organisms and taking a Stimulus-Organism-Response theory perspective, this paper identifies different types of firm-solicited and firm-unsolicited online customer engagement behaviors that act as stimuli for artificial intelligence organisms to process customer-related information resulting in both artificial intelligence and human responses which, in turn, shape the contexts of future online customer engagement behaviors.

Keywords: Artificial intelligence, online customer engagement behaviors, stimulus-organism-response, information processing systems

1.0 INTRODUCTION

The increasing use of artificial intelligence technologies is enabling organizations to manage large amounts of data in real time. Artificial intelligence can be broadly defined as a technology, or machine, that can perform a task which if conducted by a human would require intelligence to complete (McCarthy et al. 1955). The adoption of artificial intelligence in different marketing processes is opening several opportunities for marketers, and it is generating interest regarding its different applications among practitioners (Fagella 2018). In line with this, marketing academics are also increasingly developing work in this area (e.g., Kumar et al. 2016; Van Doorn et al. 2017).

Information processing systems enabled by artificial intelligence are improving the impact of marketing activities. For example, artificial intelligence enables the segmentation of social media users (Culotta, Kumar, and Cutler 2015), and boosts sales and improves the selling process (Syam and Sharma 2018). While most of the marketing interest in this area focuses on consumer responses to artificial intelligence, its practice and application, the outcomes of this fourth industrial revolution remain open to several possibilities (Syam and Sharma 2018). Therefore, this paper aims to conceptualize new ways in which artificial intelligence systems can be used to enhance online customer engagement behaviors.

We portray customer engagement behavior as a subset of a wider discussion on actor engagement (Alexander, Jaakkola, and Hollebeek, 2018; Storbacka, Brodie, Böhmann, Maglio, and Nenonen, 2016). These studies regard actor engagement as the micro-foundation of value co-creation, where "value is always co-created, jointly and reciprocally, in interactions among providers and beneficiaries through the integration of resources and application of competences" (Vargo, Margo and Akaka 2008: 146). A*ctor engagement* refers to both the actor's propensity to engage and the actor's involvement in these interactive, value co-creating resource integration activities. Importantly, providers and beneficiaries are not limited to humans and organizations but can be extended to machines and various combinations of humans, machines, and organizations (Storbacka et al., 2016).

Based on the abovementioned conceptualization of actor engagement, it is understood that customers and organizations may rely on machines or other human-made technologies in value co-creation, and can engage and interact with each other via technology, such as an online platform. Within actor engagement, it is possible to focus on specific actor groups, such as customers. One of the consequences of the growing number of interactions between customers and organizations online is the increase in the number and type of engagement behavior(s). Online customer engagement may be regarded as customers' behavioral manifestations in an online context that occur as a result of customers' motivational drivers while having a firm or brand focus (see Van Doorn et al. 2010). While new technologies have brought more ways for customers to interact with brands and companies, digital technologies have similarly enabled the automation of a company's interactions with customers. Kunz et al. (2017) develop a typology for customer engagement behaviors and suggest that customer engagement can be either customer-initiated, firm-initiated, collaborative, or passive. Kunz et al. (2017) argue that collecting big data from these four types of engagement and analyzing them can be a source of competitive advantage for firms by increasing the firm's and the customer value simultaneously. However, contrary to our study, their work does not distinguish between *solicited* and *unsolicited* engagement data, which emerges for instance from social media platforms. This distinction is important because the underlying motivations behind solicited and unsolicited manifestations of engagement differ (Beckers et al. 2018). Moreover, while highlighting the link between customer engagement behaviors and big data, Kunz et al. (2017) do not clarify how customer engagement big data are analyzed by the company. One of the challenges faced as a result of the growing amount of data available is how to process this data and measure it so that it can provide valuable insights. Fortunately, artificial intelligence technologies enable service providers to manage and react to vast amounts of data in real time, and subsequently automate service interactions. This can, in turn, provide the customized experience that is highly valued by consumers (Lemon and Verhoef 2016).

In order to theorize novel ways in which online behavioral customer engagement can be enhanced by the use of artificial intelligence systems we return to the metaphor of these systems as a living organism. The use of metaphors to develop our understanding of complex and uncertain phenomena is common when advancing theory in management research (Hunt and Menon 1995). Metaphors are defined as a mapping of entities, structures, and relations from one domain onto a different one (Hunt and Menon 1995). Thus, in this paper, we apply the Stimuli-Organism-Response theory as an 'enabling theory' to explain the relationships between both solicited and unsolicited online customer engagement behavior (Stimuli), an artificial intelligence organism (Organism), and artificial intelligence and human responses (Responses). More generally, this paper presents a conceptual framework of how online customer engagement behavior facilitates information systems enabled by artificial intelligence, which in turn drives responses, which feed into online customer engagement behaviors.

2.0 LITERATURE REVIEW

2.1 Artificial Intelligence

The concept of artificial intelligence assumes that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al. 1955, p. 1). This includes language, forming abstractions and concepts, problem-solving, pattern recognition, and learning (thereby continually developing and adapting to changing circumstances). Huang and Rust (2018) argue that there are four types of artificial intelligence, namely mechanical (i.e., automation), analytical (i.e., propensity modelling), intuitive (i.e., generation of content) and empathetic (i.e., social robotics). Therefore, the location and mobility of artificial intelligence is not only embodied within a machine (robotics) but can also be distributed within a system. Examples are increasingly common, for instance when a user types a query into a search engine, and the system figures out which results to show (Domingos 2015).

Artificial intelligence has several advantages compared to computer-enabled automations, as it can learn which parts of the data are the most predictive (Sterne 2017). Additionally, it can develop itself based on new information or as a result of experimentation. All this can happen at a scale that a human would not be able to compute, and it has therefore been suggested that technologies enabled by artificial intelligence can become a clear source of competitive advantage for organizations (Kumar et al. 2016).

Prior studies on artificial intelligence in service and marketing research have not addressed customer engagement (Kaartemo and Helkkula 2018). Therefore, the authors specifically called for more research to answer the question: “What are the ways to improve customer engagement through AI?” (Kaartemo and Helkkula 2018, p. 11). Instead of merely referring to traditional recommender systems enabled by artificial intelligence that guide customers to make choices, this study focuses on how information systems enabled by artificial intelligence can help organizations to make decisions that improve customer engagement.

2.2 Customer Engagement

2.2.1 Introduction and definition

The concept of engagement has been a subject of interest for researchers in various fields, including marketing, management, psychology, and information systems. In the marketing literature, Brodie et al. (2011) are amongst the first to provide a definition of customer engagement and argue that it is a multi-dimensional, psychological state comprising customer's cognitive, emotional, and behavioral engagement that occurs by interactive, co-creative customer experiences with a focal agent and/or object in a service relationship. In line with this argument, Hollebeek (2011, p. 785) defines customer brand engagement as "the level of a customer's motivational, brand-related and context-dependent state of mind, characterized by specific levels of cognitive, emotional and behavioral activity in brands".

While recognizing the importance of the psychological state (i.e., cognition and emotions), other scholars focus instead on the *behavioral aspect* of engagement (e.g., Van Doorn et al. 2010; Jaakkola and Alexander 2014). Behavioral customer engagement is of importance for the firm because it can have a constructive or detrimental impact on the firm, context, and individuals themselves (Van Doorn et al. 2010). Customer engagement is hence a desired outcome of a firm's marketing activities as it has been associated with other valuable outcomes to the firm (Pansari and Kumar 2017).

2.3 Online Behavioral Customer Engagement

Online behavioral customer engagement occurs as a result of the rise of the new media and the advancement of technology, which have changed the way customers connect and interact with firms (Jahn and Kunz 2012). One of the most omnipresent channels for this is social media (Gummerus et al. 2012) where customers talk about their experiences, share information, review brands and manifest enthusiasm, delight, or disgust about a brand with others (Hollebeek and Chen 2014). Online customer engagement behaviors, either over social media platforms or firm-hosted brand communities can be regarded as customers' positive and negative self-expressions about the firm, their products and services (Hollebeek and Chen

2014). These behaviors can not only have an impact on customer retention and customer life-time value (Verhoef, Reinartz, and Krafft 2010) but also enable firms to collect valuable data and insights, which in turn help firms to handle complaints, as well as managing their reputation and intelligence (Kunz et al. 2017).

2.4 Customer/Firm Involvement in Online Customer Engagement Behavior

Online customer engagement can take four forms: collaborative, firm-initiated, customer-initiated, and passive customer engagement (Kunz et al. 2017) depending on the level and depth of both customer and firm involvement in online behavioral customer engagement (see Figure 1, also see Wirtz et al. 2013).

Collaborative customer engagement occurs when there is a high level of engagement from the customers as well as the firm, and both parties contribute towards the co-creation of value (Weinberg et al. 2015; Kunz et al. 2017). As such, some authors (e.g., Bijmolt et al. 2010) refer to this type of engagement as 'co-creation', which requires some degree of participation from customers and the firm. These behaviors have a longer term focus with the primary aim being the value creation for the firm as well as the customer (Hoyer et al. 2010).

The *firm-initiated* customer engagement requires a high level of investment and initiation by the firm but not necessarily by the customer. For this purpose, companies might create a profile/page on social networks to build an audience and start a conversation amongst customers about the firm or brand (Smith, Fischer, and Yongjian. 2012). The *customer-initiated* customer engagement refers to user-generated content and takes place when customers engage in online behaviors, such as starting their own brand community, blogging, writing online reviews, and spreading brand recommendations via word of mouth, with no support or solicitation from the company (Kunz et al. 2017).

Passive engagement happens when customer and firm investment and participation are minimal (Kunz et al. 2017). An example of this is when customers are mere observers of brand communications or brand-related stimuli, which are not designed to actively or behaviorally engage customers (e.g., TV commercials) (Maslowska, Malthouse, and Collinger 2016). In passive engagement, there is no dialogue between the firm and its customers (Kunz et al. 2017; Maslowska et al. 2016). The data generated through collaborative, firm-initiated, and passive engagement are solicited by the firm, whereas the data generated by customer-initiated engagement are unsolicited (Beckers, van Doorn, and Verhoef 2018).

These four types of online customer engagement behaviors can enhance the firm's relationship with its customers (Fournier and Lee 2009). Online behavioral customer engagement data is the firm's gateway to customer's voice as they provide valuable insight into the strengths and weaknesses of the firm's new and existing offerings (Kumar et al. 2013). Aggregation of individual-level engagement data (i.e., customer choices and preferences) can create higher levels of value co-creation and reinforce further online customer engagement behaviors (Koren et al. 2008). Moreover, collection and analysis of this data allow firms to support the customer's decision-making process by providing suggestions, helping them to make a decision that is a better fit with their needs (Kunz et al. 2017). Online customer engagement data can be the backbone of a company's strategic marketing plans; companies can add targeted features to their existing products or develop new products based on customers' preferences (Kunz et al. 2017).

Until recently, one of the main challenges for companies has been collecting and aggregating customer engagement data generated through the solicited and unsolicited engagement behaviors (Choudhurry and Harrigan 2014). However, technology now allows companies to handle a high volume of customer engagement live data, which, due to its volume, can fall under the category of big data. With the advancement of machine learning and artificial intelligence use, companies can now analyze and make sense of customer engagement behavior-related big data (Akter and Waba 2016). Analysis of this big data, either coming live from the customer or being retrieved from stored databases, plays a pivotal role in creating further positive value for the firm and the customer over time, as this type of data are a rich source of advanced customer analytics (Kitchens et al. 2018). Analysis of this big data can also improve the return on investment of marketing activities (Wedel and Kannan 2016), allow firms to offer more personalized content to customers (Kumar et al. 2013), facilitate timely responses to changes in customers' content preferences, and can help the company in its future customer engagement strategy (Kunz et al. 2017).

Therefore, companies can adopt more advanced analytics enabled by artificial intelligence for a superior understanding of their customers and for the differentiation of their offerings from their competitors (Kitchens et al. 2018). However, to achieve this, companies should have the capacity to combine rich data from outside and from within their organization. Nevertheless, the key challenge resides in the company's capacity to identify, collect, integrate, and later analyze the data (Kitchens et al. 2018). Therefore, the question that remains unanswered is how this can be achieved to improve the outcome of solicited and unsolicited online customer engagement behaviors. The following section theorizes a possible solution to this problem and develops a conceptual framework that outlines how this data can be used and enhanced to produce useful results for the company.

3.0 CONCEPTUAL FRAMEWORK

3.1 Stimuli-Organism-Response Theory

The Stimuli-Organism-Response theory posits that stimuli from the environment are processed by organisms at cognitive, affective, and physiological levels leading to behavioral avoidance or approach responses (Mehrabian and Russell 1974). This theory has been widely applied to examine customers' interaction with the environment in both online (Waite and Rowley 2014; Eroglu et al. 2001) and offline settings (Chiu et al. 2005). This theory has also been adopted in marketing and service research to develop the concept of *servicescapes*, usually referred to as the 'service environment' (Bonnin 2006; Bitner 1992). Research has focused on how the management of the physical setting where a firm interacts with its customers (also known as 'atmospherics') affects their responses. Kotler (1973, p. 50) defines atmospherics as "the conscious designing of space to create certain effects in buyers". Most of the research in this area has focused on the influence of the stimuli on customers, however, there is also an acknowledgement that the stimuli may affect both customers' and employees' responses (Bitner 1992). Heavily influenced by its offline roots, stimuli have been classified in different dimensions. Some investigate the characteristics of the environment in which the interaction takes place, and identify elements such as facilities' exteriors, interiors, and other tangibles as important stimuli (Bitner 1992). In digital environments, Waite and Rowley (2014) extend the stimuli to ambient conditions such as speed of connection and website availability, but also recognize the existence of more active signs and artifacts such as customer-generated content and comments, which are considered manifestations of customer engagement (Verhoef et al. 2010). Aligned with this view that artifacts created by customers can represent stimuli, in this paper we conceptualize the different engagement behaviors that can be used as input for the systems enabled by artificial intelligence to process.

Applying a Stimulus-Organism-Response perspective on information processing systems enabled by artificial intelligence (Organisms) can provide a strong framework to theorize how customer and company interactions enabled by artificial intelligence can be enhanced and developed. The metaphoric view of artificial intelligence systems as organic is already emerging in the computer science literature to conceptualize and operationalize the new functionalities that these artificial intelligence systems can perform. For example, Gamberini and Spagnolli (2016) extend the view of symbiotic relationships from biology to conceptualize how human– artificial intelligence system relationships are developing. They argue that, as technological advancements are enabling artificial intelligence systems to collect users' data, which is consciously and unconsciously made available by users, this then allows artificial intelligence systems to elaborate solutions and make decisions based on that data. It is important to acknowledge that not all the cognitive, affective, and physiological internal processes found in the literature (Bitner 1992; Eroglu et al. 2001) are at the same level as their organic counterparts. Currently, information processing systems enabled by artificial intelligence have some limitations when processing the stimuli at affective or physiological levels. Affective stimuli would include pleasure, arousal, and dominance dimensions (Mehrabian and Russel 1974), whereas physiological stimuli would comprise human needs such as hunger, pain, and comfort (Bitner 1992). However, current work on physiological computing underpinned by advancements in physiological sensors as well as machine learning is creating systems that develop deeper mutual relationships between humans and the machines that process these signals (Jacucci et al. 2015). Furthermore, cognitive stimuli and responses can already be processed and emulated by systems enabled by artificial intelligence, and developing human-like intelligence remains the main objective of this type of system (Huan and Rust 2018). These types of internal processes can include beliefs and categorizations that the organism processes, leading to a behavioral response (Bitner 1992). In the Stimuli-Organism-Response theory, the response takes the form of approach and avoidance behaviors. In the case of the artificial intelligence organisms, the approach and avoidance responses would be related to the enhancement or hindrance of online customer engagement behaviors with their responses.

Figure 1 illustrates our conceptual framework, where we identify as stimuli both solicited and unsolicited manifestations of online customer engagement behaviors. These manifestations drive the artificial intelligence organism process, which in turn translates into artificial intelligence and human responses. The following sections examine each of these components.

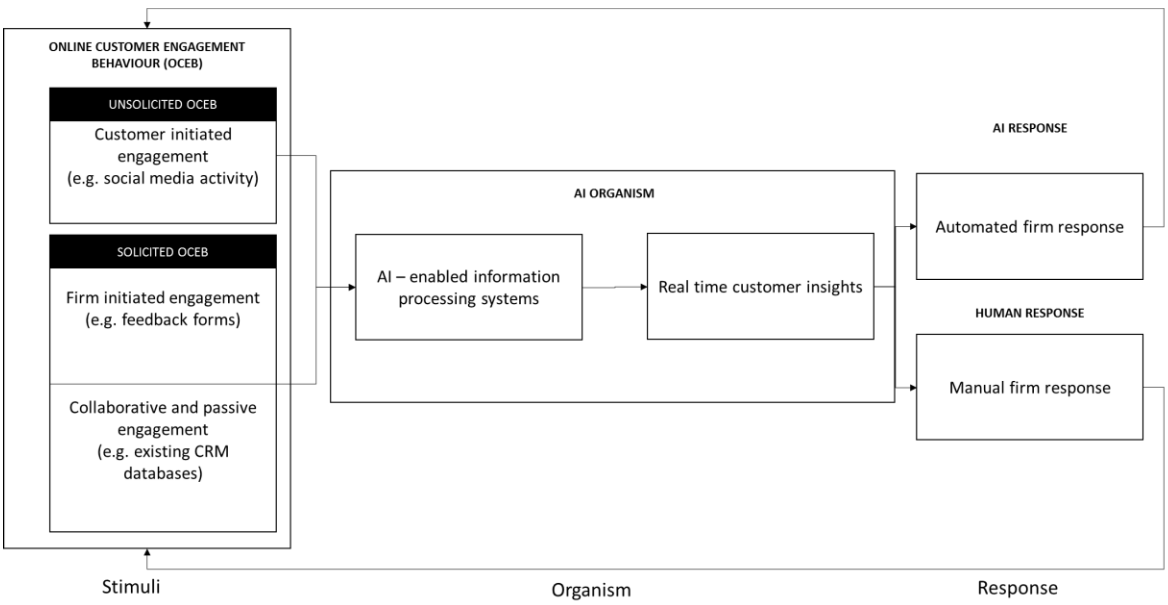

Figure 1- Conceptual Framework

3.2 Stimuli

In our model, stimuli comprise different forms of engagement that we classify based on whether it is unsolicited or solicited by the firm. Both forms of online customer engagement behavior naturally exist in digital settings, and the literature has mainly focused on understanding the mechanisms associated with the unsolicited engagement behaviors, for instance on brand communities initiated and run by customers, while practitioners have focused on devising strategies to elicit solicited engagement behavior among their customers, for instance on firm-hosted online brand communities (Marbach, Lages, and Nunan 2016). Building on Kunz et al.'s (2017) typology of online customer engagement we explain the differences between unsolicited and solicited forms of online customer engagement behavior in the following sections.

3.3 Unsolicited Online Customer Engagement Behaviors

Customer engagement initiated by the customer is introduced in this paper as *unsolicited customer engagement behaviors*, which comprise the behaviors that the customer exhibits with regard to a brand or a firm that surpass the actual transaction, without the company asking the customer to do so (Verhoef et al. 2010, p. 247). Unsolicited customer engagement occurs as a result of the internal motivational state of individuals (Beckers et al. 2018) and is likely to take place over social media platforms (Trusov et al. 2009; Zhu et al. 2016). It is usually regarded as user-generated content, where social media platforms allow customers to express themselves and communicate with others with regards to a brand or a company (Smith et al. 2012). This type of customer engagement may be individually or collaboratively generated, edited, and shared (Smith et al. 2012) and can also be either positively or negatively valenced (Henning-Thurau et al. 2004).

3.4 Solicited Online Customer Engagement Behaviors

The collaborative, passive customer engagement and firm-driven customer engagement from Kunz et al.'s (2017) typology are introduced in this study as the *solicited stored customer engagement behaviors* and *solicited live customer engagement behaviors* respectively. The solicited stored collaborative and passive data are collected from the personal devices of the customer, such as personal computers and/or smartwatches. Customers are passively engaged when they are exposed to, or are the observer of, a brand/firm communication on their personal devices, information which has little personal-goal relevance to them (Maslowska et al. 2016). Moreover, if a company produces and sells wearable devices such as smartwatches, the effective use of those depends on the customer–firm collaboration and the customer's degree of involvement with the product. The customer can use the device to track his or her daily physical activities, thus providing and sharing physiological stimuli. Moreover, with the consent of the customer, data collected from the wearable device are sent to the company and stored on the company's databases. Likewise, data from the previous interactions of the customer with the company (both collaborative and passive customer engagement) are also stored on the existing customer relationship management databases, which can be of value for the company in informing its future relationships with its customers.

Firm-initiated customer engagement behaviors are introduced as *solicited live customer engagement behaviors*, which occur as a result of the company's strategies and initiatives to leverage customer engagement (Kunz et al. 2017). Similar to the solicited collaborative stored customer engagement, the solicited live customer engagement is interactive and requires some degree of participation from the customers or members (Beckers et al. 2018). This internal feedback, along with reviews provided directly to the company, are also known as the 'customer's voice', which allows companies to identify any potential defects in their new products or service offerings (Assaf et al. 2015; Hirschman 1970), which is beneficial for the company in the long run.

Proposition 1: A combination of unsolicited and solicited online customer engagement data is a better source of input for the artificial intelligence organism to provide real-time insights and suggestions for actions than either one on its own.

3.5 Organism

3.5.1 Information processing systems enabled by artificial intelligence

Information processing systems enabled by artificial intelligence can give companies real-time insights and also provide suggestions for action. Recommender systems give advice to customers on what to buy, watch or listen to, based on data about the company's available items and their previous transactions (Ricci, Rokach, and Shapira 2015). First, this can be in the form of non-personalized recommendations, such as the top ten best-selling books. Secondly, there can be personalized recommendations based on the system's previous information about the customer. The recommender system can make suggestions in different ways: by memorizing earlier combinations, by generating new combinations through deep neural network generalization, or by combining both memorization and generalization (Cheng et al. 2016).

Information processing systems enabled by artificial intelligence normally base their algorithms on past data from the user. Isinkaye et al. (2015) suggest that there are three types of data processing methods in recommendation systems: content-based, collaborative, and hybrid. *Content-based* data processing is also known as 'cognitive filtering', which uses customer metadata (e.g., likes, user pre-defined preferences) as well as data input by the user in real time (e.g., search terms on Google). *Collaborative recommendations* use the ratings or user's purchase history to compare different users. The distance between the pairs of users is calculated and then the closest individual user is matched to other users (i.e., users who have similar tastes) (Herlocker et al. 2004). Finally, *hybrid recommendations* blend elements of content-based and collaborative recommendations. Recommendation systems enabled by artificial intelligence provide personalized products to customers making their buying/consuming decision quick and easy. Along with data richness, information overload becomes a problem (Chen, et al. 2009).

While conventional recommender systems are designed for advising customers by helping them make decisions, decision support systems can be employed for recommending actions for service providers. For instance, Chica and Rand (2017) present a set of guidelines and recommendations to guide the construction of a successful decision support system for word of mouth. In their model, Chica and Rand (2017) do not explicitly link their decision support systems model with artificial intelligence and delimit their discussion to word of mouth, they suggest that data-driven analysis of customer engagement behavior can provide real-time customer insights for companies. Villaroel Ordenes et al. (2014), in turn, developed a holistic approach to analyzing customer feedback by incorporating elements of customer experience, namely activities, resources, and context. They applied text mining (analysis of textual information) to evaluate how interactive service processes influence customer experiences. In addition to live customer engagement behaviors, companies typically store various information in their customer relationship management system about a customer's history with a company. In the past, this information has been particularly useful for predicting customer churn (Vafeiadis et al. 2015). We argue that by combining live (unsolicited and solicited) data with stored customer relationship management data, there is a higher probability of moving beyond predicting customer behavior to understanding and enhancing customer engagement behavior. Whereas the combination of the data sources could not be efficiently done by a human, information processing systems enabled by artificial intelligence allow companies to develop real-time customer insights.

Proposition 2: A combination of live and stored data processed by artificial intelligence systems provides more comprehensive real-time customer insights than relying solely on either one or the other.

3.5.2 Real-time customer insights

A customer-centric marketing approach aims to understand and satisfy the needs and wants of individual customers rather than focusing on large market segments. To achieve this customer-centric approach, obtaining consumer insights becomes central to the development of marketing strategies (Fulgoni 2014). The process of obtaining consumer insights involves gathering data and structuring it so that it becomes useful information. This process, also known as ‘business intelligence’ (Chen et al. 2012), leads to consumer insights that marketers can use for inspiration and the development of marketing strategies (Fortini-Campbell 1992). Real-time customer insights can be gained, for instance, by collecting and analyzing blog posts and blogger communities (Chau and Xu 2012).

Traditionally, business intelligence was done in an asynchronous manner, that is, there was a delay between the data collection for primary market research, the analysis of aggregated information coming from data sources (e.g., point of sales data, feedback from customers), and the subsequent implementation or change of marketing activities. This delay can be decisive, as, for instance, a fast reaction to service failure positively influences customer engagement (such as repatronage intentions and word-of-mouth behavior) (Wirtz and Mattila 2004). Also, customer preferences tend to change over time (Sahoo et al. 2012). Underpinned by technological advancements, the capability to collect and process customer data in real time is leading to more interactive customer–company relationships (Greenberg 2010) with automated firm responses to service interactions. This is enabled by sentiment and category analysis.

Proposition 3: Real-time customer insights trigger artificial intelligence and human responses to enhance future online customer engagement behavior.

3.5.3 Sentiment and category analysis

Sentiment analysis involves the computational treatment of opinions, sentiments and subjectivity in written form (Pang and Lee, 2008). Sentiment analysis can be conducted by using dictionaries containing words that refer to a sentiment or topic categories. These dictionaries can be readily available, but they can also be built using training material to classify texts based on their polarity (positive or negative). While sentiment analysis can be important in informing managers about levels of customer satisfaction, it may be that the reasons vary from one customer to another. Therefore, it is important to run a category analysis to find out whether or not customers are happy with certain features, such as price or customer service (Oelke et al. 2009). Category analysis helps to classify the text into certain topics that the feedback or sentiments refer to (Sebastiani, 2002). Through machine learning, it is possible to categorize a message belonging, for instance, to a certain department in a hardware store, a moment in a customer journey, or certain aspect of a product. This helps companies to identify the people who should react to the feedback in the organization. Prior literature indicates that customer feedback can be found in different categories, such as product features, price, or delivery time (Ziegler, Skubacz, and Viermetz 2008). Villaroel Ordenes et al. (2014), in turn, categorized customer experience feedback in terms of activities, resources, and situational and personal context. While the idea of combining sentiment and category analysis for evaluating customer feedback has been proposed, the empirical data and the models are specific to the situation and the type of service (Villaroel Ordenes et al. 2014). While prior literature suggests that the sentiment and category analysis should be linked with the analysis of customer lifetime value (Villaroel Ordenes et al. 2014), we argue that it is not only the customer feedback but the company’s response to the feedback that should bring positive results in customer engagement.

Proposition 4: A combination of sentiment and category analysis provides more comprehensive results on future online customer engagement behavior than relying solely on either one alone.

3.6 Response

In line with the Stimuli-Organism-Response theory perspective of this paper, the insights gained from stimuli that are processed by the artificial intelligence organism lead to several artificial intelligence responses to online customer engagement behaviors. As a result, companies can employ various marketing communication tools, such as advertising, public relations, direct marketing and personal selling, price deals, or social media posts (Fill and Turnbull 2016). Particularly, artificial intelligence enables companies to apply more targeted and personalized communication, which is expected to influence customer engagement behavior (Chen et al. 2012).

In the past, managers needed to make decisions on what marketing strategies were developed, based on the business intelligence process (Li et al. 2008). Nowadays, the company can respond to customer insights in two ways: manually and automatically. In the following sections, we discuss both types of responses.

3.6.1 Manual firm response

Information processing systems enabled by artificial intelligence identify the appropriate people in the organization to respond to the customer insight. For instance, if there is negative customer (solicited or unsolicited) feedback regarding customer service or a certain product in an e-commerce site, category analysis performed by artificial intelligence systems understands the context of the feedback. Thus, the customer insight can be directed to the correct person. Further, if the customer’s feedback is linked with customer relationship management data, it is possible to provide a more detailed response, and automatically forward the feedback to the manufacturer of the product, whose representative can respond to it.

For instance, in a case where the artificial intelligence identifies a high churn risk in feedback, the response is handled by a real person and, if the feedback is positive, the response to the customer can be entirely automated; that is, if a person is using a subscription model web service, a certain type of behavior and negative feedback can predict a higher risk to churn. This prediction is based on the analysis that the algorithm makes on previous existing data, and patterns are therefore identified that are regularly undetected by humans (Freitag 2000). Once the risk of churn is flagged by the information processing system enabled by artificial intelligence, the case can be handled by a human customer representative.

3.6.2 Automated firm responses

In addition to providing insight for manual responses, the artificial intelligence reduces the time between data collection and decision-making on how these responses are written and triggered, enabling automated, targeted, and personalized communication without human intervention. This is revolutionary compared to the automated customer service telephone lines of yesteryear or other automated business functions (see Karimi, Somers, and Gupta 2001). Here, we do not refer to mere interaction with frontline robots (Marinova et al. 2017; van Doorn et al. 2017). Instead, we perceive automated firm responses as any non-human, real-time customer interaction, which is based on the analysis of various integrated data sources on customer engagement and prior evidence on the impact of similar responses with past customers.

There are several benefits of using responses in customer–firm interactions enabled by artificial intelligence. For instance, with feedback in certain areas of business, such as customer service, the artificial intelligence can decide which feedback can be answered automatically. In e-commerce, positive product feedback does not necessarily require direct response to the customer, whereas negative feedback would require a personalized answer and possibly further questions. This communication can be then automated. If the artificial intelligence recognizes the feedback to be especially positive and relates to the service or product sold, the data can then be used in marketing to create reviews automatically. Right after the feedback is submitted, the data are analyzed and, if positive, the customer can be asked to share that information on social media creating in this way positive word of mouth.

Proposition 5: A combination of manual and automated responses enhance future online customer engagement behaviors more than relying solely on either one or the other.

In sum, our conceptual framework aimed to integrate two bodies of literature, namely customer engagement and artificial intelligence, for which new applications and implications are still understudied (Kunz et al 2017). By using a Stimuli-Organism-Response theory perspective to integrate these two elements, this study provides several theoretical contributions and managerial implications derived from our conceptual framework, which are discussed in the following section.

4.0 THEORETICAL CONTRIBUTIONS AND MANAGERIAL IMPLICATIONS

One of the theoretical contributions of this paper is our application of the Stimuli-Organism-Response theory to a non-human organism. Systems enabled by artificial intelligence aim to replicate human cognition and behavior, and as their ability to do so improves, their capabilities become closer to those of humans than mere computer systems. Huang and Rust (2018) already argue that artificial intelligence systems are capable of analytical, intuitive, and even empathetic intelligence, and, in fact, the internal processes that occur in artificial intelligence systems and machine learning algorithms are different from traditional programming code

(Domingos 2015). Artificial intelligence system data act as stimuli that is synthesized, and that help the system learn and adapt to the most efficient and appropriate process in performing a response; whereas in traditional computer systems a detailed instruction (a program) is written and performed by the computer without adaptation or learning taking place. For this reason, we argue that the response to stimuli from the environment in which artificial intelligence systems are in place should also be examined using theories that were initially developed for living organisms.

Secondly, anchored in the metaphoric view of artificial intelligence systems as organismic systems and in Stimulus-Organism-Response theory, this study proposes an integrative conceptual framework linking two bodies of research – customer engagement and artificial intelligence – which have largely been investigated separately thus far. Hence, we provide a theoretical contribution to the marketing literature by "integrating" these two previously distinct bodies of literature (MacInnis 2011, p. 138).

Thirdly, by increasing one's understanding of the theoretical relationships surrounding the concept of customer engagement, further empirical research of customer engagement can be developed (Hollebeek, Srivastava and Chen 2016). Fourthly, this study responds to Kunz et al.'s (2017) call for research on the fit between firm and customer engagement behaviors by further investigating the dynamic nature of feedback loops between artificial intelligence and human responses, and future online customer engagement behaviors. Fifthly, this study further develops Kunz et al.'s (2017) online customer engagement behaviors' typology – namely passive, collaborative, customer-initiated and firm-initiated customer engagement – by arguing that these types of online customer engagement behaviors can be either solicited (live and stored) or unsolicited by the organization, determining whether the data exist on the company's databases or on third parties' online platforms. This further categorization allows us to discuss that a non-human agent can gather data from different types of customer engagement from existing company-owned databases, real-time company-owned customer engagement data, customer engagement data on third-party platforms, and subsequently make sense of and provide appropriate responses to the data in real time.

Sixthly, while Rust and Huang (2014) have recognized the importance of machine learning in processing data quickly and automatically for personalized services, the link between automated firm responses enabled by artificial intelligence and customer engagement behavior remains undeveloped in service and marketing research. There is a lack of discussion on how companies can utilize customer data to make customer communication (whether it is marketing or customer support) more personalized. We contribute to the unanswered questions on personalization (Rust and Huang 2014, p. 216) by further investigating how artificial intelligence and machine learning are actually utilized in the area of customer engagement. Thus, our study provides both the theoretical contributions discussed previously and the practical implications discussed next.

Seventhly, in the context of artificial intelligence, this research contributes to the discussion by having a closer look at the role of artificial intelligence in responding to customer feedback. The idea of developing an automated system for mining online customer feedback data is not new (Bhuiyan, Xu, and Josang 2009). However, while the extant research has built models on implicit customer feedback, such as sales and utilizing recorded data (Bauer and Nanopoulos 2014), we, uniquely, suggest combining explicit and implicit data. Our study provides a clear direction on how solicited and unsolicited sources of information can be integrated and directed towards systems enabled by artificial intelligence to enhance a firm's responses in the form of customized automated responses and human responses. As a result, the study answers the call by Syam and Sharma (2018) to gain a better understanding of how artificial intelligence and machine learning can improve sales management and personal selling, particularly in terms of prospecting and approaching customers.

Our conceptual study hence provides several thoughts on the managerial implications for companies on how to employ artificial intelligence for facilitating customer engagement. First, we suggest that artificial intelligence-enabled information processing may allow companies to combine live (solicited and unsolicited) and stored customer relationship management data sources. Currently, companies tend to analyze each data source separately. The categorization enabled by artificial intelligence of solicited and unsolicited data could allow companies to identify trends on the nature and valence of online customer engagement behavior. The analysis performed by systems enabled by artificial intelligence on online customer engagement behaviors might also allow companies to identify the relative importance of each product aspect and how much it impacts customer engagement. Understanding the relative importance of these elements would then help companies to put more effort into the development of more impactful features of the customer journey. Also, systems enabled by artificial intelligence could be able to understand the meaning of online customer engagement behaviors that are in a written format which would help to interpret the feedback.

Secondly, analysis of customer engagement enabled by artificial intelligence could allow companies to make improvements in different parts of the service by providing customer insight in real time to the appropriate people in the organization. Artificial intelligence could help companies to process vast amounts of feedback using Machine learning algorithms to organize and assign sentiment scores to incoming, open text feedback as it arrives in the firm's systems. This means that companies can monitor in real time which areas of the business can be improved. Artificial intelligence could also facilitate the process for companies to manage online customer engagement behaviors directed to the firm, and to make sure that they are directed in real time to the appropriate department, without the need for the customer to pay any particular action. Thirdly, we underline in our conceptual framework that responding to customer insight does not necessarily require manual labor. Companies could save time and resources by automating various responses to their customers depending on customer insights. This also relates to the envisioned, predictive insights from their customers' feedback and react automatically to their needs before unsatisfied customers decide to end the business relationship. Fourthly, our conceptual framework links the firm responses (both manual and automated) with customer engagement behavior. Consequently, artificial intelligence could learn what kind of responses are more profitable for each customer persona. Theoretically, this enables the creation of automated responses and guides managers and staff to react to customer insight in a way that facilitates customer engagement and increases the profitability of the company.

5. 0 CONCLUSION AND FUTURE RESEARCH

We conclude by suggesting that future theory development in artificial intelligence systems should be informed by information system theories, but that the use of richer theories that aim to explain human behavior can be appropriate to guide the development of applications for these new technologies, especially since these technologies are designed to emulate human-like responses. They are increasingly achieving this goal by using a large amount of data as stimuli.

In terms of additional future research, our conceptual framework presents a unique idea where various forms of data sources (solicited and unsolicited) containing manifestations of online customer engagement are integrated to be analyzed by systems enabled by artificial intelligence. More research is also needed to expand our understanding of online customer engagement behavior, in particular in terms of how customized responses from the firm enabled by artificial intelligence can impact on the outcomes that the literature has found in other forms of customer engagement. We recommend that both managers and academics looking to implement our framework gather information from several industries as this can improve the learning of information processing systems enabled by artificial intelligence and improve their responses. Future empirical research will also help in developing more detailed managerial implications on how to enhance online customer engagement behavior.

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