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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.

1. 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, Minsky, Rochester, & Shannon, 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, Dixit, Javalgi, & Dass, 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, & Cutler, 2015), and boosts sales and improves the selling process (Syam & 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 & 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, & Hollebeek, 2018; Storbacka, Brodie, Böhm, Maglio, & 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, Maglio, & Akaka, 2008: 146). Actor 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, van Doorn, & Verhoef, 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 & 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 & Menon, 1995). Metaphors are defined as a mapping of entities, structures, and relations from one domain onto a different one (Hunt & 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. 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 Russ (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 & 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 & 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, Hollebeek, Jurić, and Ilić (2011) are amongst the first to provide a definition of customer engagement and argue that it is a multidimensional, 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., Jaakkola & Alexander, 2014; van Doorn et al., 2010). 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 & 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 & Kunz, 2012). One of the most omnipresent channels for this is social media (Gummerus, Liljander, Weman, & Pilhström, 2012) where customers talk about their experiences, share information, review brands and manifest enthusiasm, delight, or disgust about a brand with others (Hollebeek & 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 & Chen, 2014). These behaviors can not only have an impact on customer retention and customer life-time value (Verhoef, Reinartz, & KRAFT, 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 Fig. 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 (Kunz et al., 2017; Weinberg, Milne, Andonova, & Hajjat, 2015). 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, Chandy, Dorotic, Krafft, & Singh, 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 and the firm. These behaviors have a longer term focus with the primary aim of engaging the firm as well as the customer (Hoyer, Chandy, Dorotic, Krafft, & Singh, 2010).

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 (Kunz et al., 2017; Weinberg, Milne, Andonova, & Hajjat, 2015). 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, Chandy, Dorotic, Krafft, & Singh, 2010).

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, & 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 et al., 2018).

These four types of online customer engagement behaviors can enhance the firm’s relationship with its customers (Fournier & Lee, 2009). Online behavioral customer engagement data is 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 (Choudhury & Harrigan, 2014). However, technology now allows companies to handle a high volume of customer engagement 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 & Wamba, 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, Dobolyi, Li, & Abbasi, 2018). Analysis of this big data can also improve the return on investment of marketing activities (Wedel & Kamak, 2016), allows 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.

![Conceptual Framework](Fig. 1. Conceptual Framework.)
3. 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 & Russell, 1974). This theory has been widely applied to examine customers’ interaction with the environment in both online (Eroglu, Machleit, & Davis, 2001; Waite & Rowley, 2014) and offline settings (Chiu, Lin, & Tang, 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’ (Bitner, 1992; Bonnin, 2006). 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 metaphorical 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 & Russell, 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, Spagnolli, Freeman, & Gamberini, 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 (Huang & 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-O rganism-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.

Fig. 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.

3.2. Stimuli

In our model, stimuli comprise different forms of engagement that we classify based on whether it is solicited 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, & 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, Bucklin, & Pauwels, 2009; Zhu, Chang, & Luo, 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 (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004).

3.4. Solicited online customer engagement behaviors

The collaborative, passive customer engagement and firm-driven customer engagement from Kunz et al. (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 (Maslovska 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


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, & 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, Folajimi, and Ojokoh (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, Konstan, Terveen, & Riedl, 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, Shang, & Rao, 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. Villarol Ordones, Theodoulidis, Burton, Gruber, and Zaki (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 (Valeiadis, Diamantaras, Sarigiannidis, & Chatzisavvas, 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, Chiang, & Storey, 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 & 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 & Mattila, 2004)). Also, customer preferences tend to change over time (Sahoo, Singh, & Mukhopadhyay, 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 & 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...
following sections, we discuss both types of responses.

3.6.1. Manual firm response

customer insights in two ways: manually and automatically. In the
unsolicited) feedback regarding customer service or a certain product in
identify the appropriate people in the organization to respond to the
(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 re-
ponses to online customer engagement behaviors. As a result, com-
panies can employ various marketing communication tools, such as
advertising, public relations, direct marketing and personal selling, price
deals, or social media posts (Fill & Turnbull, 2016). Particularly, arti-
ficial 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, Shue, & Lee, 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 intelli-
genence 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 automati-
cally 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, & Gupta, 2001). Here, we do not refer to
mere interaction with frontline robots (Marinova, de Ruyter, Huang,
Meuter, & Challagalla, 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 inte-
grated 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 in-
teractions enabled by artificial intelligence. For instance, with feedback
in certain areas of business, such as customer service, the artificial in-
telligence 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 ser-
vice or product sold, the data can then be used in marketing to create
events 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. 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. Sys-
tems 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 pro-
gramming 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 pro-
gram) 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 link-
ing two bodies of research – customer engagement and artificial intel-
ligence – 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
(MacLennan, 2011, p. 138).

Thirdly, by increasing one’s understanding of the theoretical re-
lationships surrounding the concept of customer engagement, further
empirical research of customer engagement can be developed
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References

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. *Electron Markets, 26*(2), 173–194.

Alexander, M. J., Jaakkola, E., & Hollebeek, L. D. (2018). Zooming out: actor engagement beyond the dyadic. *Journal of Service Management, 29*(3), 333–351.

Assaf, A. G., Josiassen, A., Knezevic Cvelbar, L., & Woo, L. (2015). The effects of customer voice on hotel performance. *International Journal of Hospitality Management, 44*, 77–83.

Bauer, J., & Nanopoulos, A. (2014). Recommender systems based on quantitative implicit customer feedback. *Decision Support Systems, 68*, 77–88.
Beckers, S. F., van Doorn, J., & Verhoef, P. C. (2018). Good, better, engaged? The effect of company-initiated customer engagement behavior on shareholder value. Journal of the Academy of Marketing Science, 46(3), 366–383.

Bhuiyan, T. X., Yu, J., & Jangos, A. (2009). State-of-the-art review on opinion mining from online customers’ feedback. In Proceedings of the 9th Asia-Pacific complex systems conference (pp. 385–390). China University.

Bijmolt, T. H. A., Leeflang, P. S. H., Blok, F. G. M., Hardie, B. G. S., Lemmens, A., & Saffert, P. (2010). Analytics for customer engagement. In Journal of Service Research, 13(3), 341–356.

Bitner, M. J. (1992). Servicescapes: The impact of physical surroundings on customers and employees. Journal of Marketing, 56(2), 57–71.

Bonnin, G. (2006). Physical environment and service experience: An appropriation-based model. Journal of Service Research, 9(4), 43–59.

Brown, J., Hollingshead, B. W., & Jairiz, R. B., & Ilic. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. Journal of Service Research, 14(3), 252–271.

Chai, X. L., & Xu, X. (2012). Business intelligence in blogs: Understanding consumer interactions and communities. MIS Quarterly, 36(4), 1189.

Chen, H., Chang, R. H., & Storey, V. C. (2012). Customer intelligence and Analytics: From big data to big impact. MIS Quarterly, 36(4), 1165–1188.

Chen, Y.-C., Shang, R.-A., & Kao, C.-T. (2009). The effects of information overload on consumers’ subjective state towards buying decision in the internet shopping environment. Electronic Commerce Research and Applications, 8(1), 48–58.

Cheng, H. T., Koc, I., Harmen, J., Shaked, T., Chandra, T., Aradhye, H., ... & Anil, R. (2016, September). Wide & deep for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems (pp. 7–10).

Chica, M., & Rand, W. (2017). Building agent-based decision support systems for word-of-mouth programs: A freemium application. Journal of Marketing Research, 54(5), 752–767.

Chiu, Y. B., Lin, C. P., & Tang, L. L. (2005). Gender differs: Assessing a model of online purchase intentions in e-tail service. Journal of Consumer Marketing, 22(2), 149–176.

Culotta, A., Kumar, N. R., & Cutler, J. (2015, January). Predicting the demographics of Twitter users from website traffic data. In Conference proceedings of the twenty-ninth AAAI conference on artificial intelligence, Austin, Texas (pp. 72–78).

Domingos, P. (2015). The master algorithm: How the quest for the ultimate learning machine will remake our world. London: Penguin.

Ergo, S. A., Macleith, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing. Journal of Retailing, 54(2), 177–188.

Fagella, D. (2018). Artificial intelligence in marketing and advertising – 5 examples of real traction [Online]. https://techemergence.com/artificial-intelligence-in-marketing-and-advertising-5-examples-of-real-traction/. Accessed 25 October 2018.

Fili, C., & Turnbull, S. I. (2016). Marketing communications: Brands, experiences and participation. London: Pearson.

Fortini-Campbell, L. (1992). The consumer insight workbook: How consumer insights can inspire better marketing and advertising. Journal of Consumer Engineering, 9(4), 73–74.

Fournier, S., & Lee, L. (2009). Getting brand communities right. In Getting brand communities right. (pp. 4). Cham: Springer.

Freitag, D. (2000). Machine learning for information extraction in informal domains.

Gummerus, J., Liljander, V., Weman, E., & Pihlström, O. (2010). Analytics for customer engagement. In Journal of Service Research, 13(4), 410–420.

Hirschman, O. E. (1970). Exit, voice, and loyalty: Responses to decline in firms, industries, and states. Cambridge, M.A.: MIT Press.

Hoyer, W. D., Chandy, R., Dorotic, M., Krafft, M., & Singh, S. S. (2010). Consumer co-creation in new product development. Journal of Service Research, 13(3), 283–296.

Jahn, B., & Kunz, W. (2012). How to transform consumers into fans of your brand. Journal of Service Management, 23(3), 344–361.

Karimi, J., Somers, T. M., & Gupta, Y. P. (2013). Differentiation and uniqueness: The role of purchase intention in service marketing. Journal of Management Information Systems, 29(4), 9–12.

Kunz, W., Aksoy, I., Bart, Y., Heinonen, K., Kababady, S., Ordenes, F. V., Theodoulidis, B., & et al. (2017). Customer engagement in a Big Data world. Journal of Services Management, 31(2), 161–171.

Kore, S. (2006). Customer engagement: Integrative framework, revised fundamental propositions, and implications for research. Journal of the Academy of Marketing Science, 47(8), 693–711.

Kore, Y. (2008). Factorization meets the neighborhood: A multifaceted collaborative filtering model. In Proceedings of the 14th ACM SIGKDD international conference on knowledge discovery and data mining, Las Vegas, Nevada.

Kotler, P. (1973). Atmospheres as a marketing tool. Journal of Retailing, 49(4), 48–64.

Kumar, V., Chattaraman, V., Neghina, C., Skiera, B., Aksoy, L., Buoye, A., & Henseler, J. (2013). Data-driven services marketing in a connected world. Journal of Service Management, 24(3), 330–356.

Kumar, V., Batra, A., Javalgi, R. B., & Dass, M. (2016). Research framework, strategies, and applications of intelligent agent technologies (IATs) in marketing. Journal of the Academy of Marketing Science, 44(1), 24–45.

Kunz, W., Aksoy, I., Bart, Y., Heinonen, K., Kababady, S., Ordenes, F. V., Theodoulidis, B., et al. (2017). Customer engagement in a Big Data world. Journal of Services Management, 31(2), 161–171.

Kimes, J. P., & Verhoeef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96.

Lee, S.-H., Chee, C., & Lee, L. (2008). Business intelligence approach to supporting strategy-making of IFP service management. Expert Systems with Applications, 35(1), 793–799.

Macniss, D. J. (2011). A framework for conceptual contributions in marketing. Journal of Marketing, 75(4), 136–157.

Marbach, J., Lages, C. R., & Nunan, D. (2016). Who are you and what do you value? Investigating the role of personality traits and customer-perceived value in online customer engagement. Journal of Marketing Management, 32(5-6), 502–525.

Martinova, D., de Ruyter, K. A., Huang, M.-H., Meuter, M. L., & Chattagalli, G. (2017). Getting smart: Learning from technology-empowered frontline interactions. Journal of Service Research, 20(1), 24–42.

Maier, E., Malthouse, E. C., & Culler, B. T. (2016). The customer engagement ecosystem. Journal of Marketing Management, 32(5-6), 469–501.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). A proposal for the Dartmouth summer research project on artificial intelligence [Online]. http://www.ai.group.dartmouth.edu/jmc/history/dartmouth/dartmouth.html. Accessed 12 November 2018.

Mehrabian, A., & Russell, J. A. (1973). An approach to environmental psychology. Cambridge, M.A.: MIT Press.

Oleke, D., Hao, M., Rohrbeck, C., Keim, D. A., Dayal, U., Haug, L. E., & Janzko, H. (2009, October). Visual opinion analysis of customer feedback data. In 2009 IEEE symposium on visual analytics science and technology (pp. 187–194). IEEE.

Pan, B., & Lee, L. (2008). Opinion mining and sentiment analysis. Foundations and Trends®: Information Retrieval, 2(1–2), 1–135.

Pansari, A., & Kumar, V. (2017). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 64(5-6), 294–311.

Pang, B., & Lee, L. (2005). Opinion mining and sentiment analysis. Foundations and Trends®: Information Retrieval, 2(1–2), 1–135.

Pansari, A., & Kumar, V. (2017). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 64(5-6), 294–311.

Pattichis, C. (2012). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 30(4), 306–317.

Pattichis, C. (2012). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 30(4), 306–317.

Pattichis, C. (2012). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 30(4), 306–317.

Pattichis, C. (2012). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 30(4), 306–317.

Pattichis, C. (2012). Customer engagement: The construct, antecedents, and consequences. Journal of Operations Management, 30(4), 306–317.
Trusov, M., Bucklin, R. E., & Paasivuo, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an internet social networking site. Journal of Marketing, 73(5), 91-102.

Vafeiadis, T., Diamantaras, K. I., Sariyanniindis, G., & Chatzisavvas, K. C. (2015). A comparison of machine learning techniques for customer churn prediction. Simulation Modelling Practice and Theory, 55, 1-19.

van Doorn, J., Lemon, R. N., Mitra, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. Journal of Service Research, 13(3), 253-266.

Van Doorn, J., Meade, M., Noble, S. M., Huiland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Dono arigato Mr. Robot: Emergence of automated social presence in organizational frontlines and customers’ service experiences. Journal of Service Research, 20(1), 43-58.

Vargo, S. L., Maglio, P. F., & Akaka, M. A. (2008). On value and value co-creation: A service systems and service logic perspective. European Management Journal, 26(3), 145-152.

Verhoef, P. C., Reinartz, W. J., & Krafft, M. (2010). Customer engagement as a new perspective in customer management. Journal of Service Research, 13(3), 247-252.

Villaroel Ordenes, F., Theodoulidis, B., Burton, J., Gruber, T., & Zaki, M. (2014). Mining and exploring unstructured customer feedback data using language models and treemap visualizations. In 2008 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology (Vol. 1, pp. 932-937). IEEE.

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