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Abstract

An increasing amount of research on Intelligent Systems/Artificial Intelligence (AI) in marketing has shown that AI is capable of mimicking humans and performing activities in an 'intelligent' manner. Considering the growing interest in AI among marketing researchers and practitioners, this review seeks to provide an overview of the trajectory of marketing and AI research fields. Building upon the review of 164 articles published in Web of Science and Scopus indexed journals, this article develops a context-specific research agenda. Our study of selected articles by means of Multiple Correspondence Analysis (MCA) procedure outlines several research avenues related to the adoption, use, and acceptance of AI technology in marketing, the role of data protection and ethics, the role of institutional support for marketing AI, as well as the revolution of the labor market and marketers' competencies.

Keywords: Artificial Intelligence, Intelligent System, Marketing, Systematic Literature Review, Multiple Correspondence Analysis, HOMALS.

THE EVOLVING ROLE OF ARTIFICIAL INTELLIGENCE IN MARKETING: A REVIEW AND RESEARCH AGENDA

1. Introduction

Research on digital and technological evolution in marketing has been considerably fast-paced (Crittenden et al., 2019), with researchers seeking to explore the ways in which technological advancements influence the knowledge potential of organizations when it comes to managing customer needs and delivering offerings (Kumar et al., 2019). The existing body of research on marketing is rich with studies assessing the effects and the application of several technologies on marketing performance. However, only in recent years has research positioned at the intersection of Artificial Intelligence (AI) and marketing been given more attention, with recent calls for research encouraging further exploration of AI-related topics and their roles in marketing (Davenport et al., 2020; Kumar et al., 2019). With this in mind, and for the purpose of this review, we adopt an understanding of AI as "computational agents that act intelligently" (Poole & Mackworth, 2010, p. 3). This notion departs from earlier views that have considered AI to be limited only to machines that can display human-like intelligence. In this regard, we embrace the definition of Marketing AI as "the development of artificial agents that, given the information they have about consumers, competitors, and the focal company, suggest and/or take marketing actions to achieve the best marketing outcome" (Overgoor et al., 2019, p. 2).

From a strategic perspective, AI is becoming increasingly important in marketing. Companies such as Google, Rare Carat, Spotify, and Under Armor are among the expanding list of firms enhancing their performance through the adoption of AI-based platforms (such as Microsoft Cognitive Services, Amazon Lex, Google Assistant, or IBM Watson). This approach increases their customer interaction across marketing channels and improves market forecasting and automation. Consequently, AI has been recognized as the most influential technology for business, with expected growth from $10.1 billion in 2018 to $126 billion by 2025 (Tractica, 2020). A recent survey among business leaders revealed that a priority area for the application of AI is in sales and marketing, with 24% of US companies already using AI and 60% expected to use it by 2022 (MIT Technology Review Insights, 2020). Additionally, AI is considered the number one workplace trend in the Society for Industrial and Organizational Psychology's workplace list (SIOP, 2020).

The success of AI in marketing practices is also reflected in research, with several significant contributions appearing in recent times, particularly from 2017 onwards. The academic attention given to AI can be traced back to the 1980s, with studies focusing on expert systems and robotics (e.g., Chablo, 1994; Davenport, 2018; Gill, 1995). After a quiet period of almost two decades, its recent popularity among researchers and practitioners within marketing can be ascribed to three major factors: the development of Big Data; the availability of computational power; and the progression of AI techniques and technological enablers (Bock et al., 2020; Overgoor et al., 2019).

Recent expert-based surveys on this topic (Davenport et al., 2020; Kumar et al., 2019; Kumar et al., 2020a) have outlined the importance of the application of AI in marketing. However, these studies are not based on a sound quantitative approach and arguably suffer from interpretative or subjectivity biases (Furrer et al., 2020). With this in mind, this study aims to complement contemporary findings by further elucidating the historical intersection of the two research fields and subsequently proposing avenues for future research. A multiple correspondence analysis (MCA) method was used in order to reveal the foundations of the research field and allow for the representation of the field's intellectual structure. This approach has been recognized as a reliable method of content analysis, enabling the mapping of the structure of various research fields, such as international strategic alliances (López-Duarte et al., 2016), service marketing (Furrer et al., 2020), and immigrant entrepreneurship (Dabić et al., 2020), among others.

This paper offers multiple contributions to the field of AI and marketing. Firstly, while the majority of previous works conducting reviews on AI and marketing can be considered structured expert-based reviews, which, although valuable, can suffer from interpretative or subjectivity biases (Furrer et al., 2020), our work relies on content analysis combined with quantitative MCA procedures. In so doing, our paper complements expert-based reviews, offering a more objective account of the development of AI and marketing. The methodology used for this study – which is, to our knowledge, the first of its kind to be applied to AI and marketing studies – allows us to delineate a research agenda related to theory, context, characteristics, and methods. While several previous studies have focused on the interaction between AI and a specific marketing area, our paper instead offers a comprehensive overview of more than 30 years' worth of development in this research field by not imposing any limitations with regards to time or topics.

The remainder of the article is structured as follows. In the following section, we outline the typology of previous systematic literature reviews and present the methodological approach adopted in our study. In Section 3, we provide an illustration of the marketing and AI research field, outlining theoretical underpinnings and major research themes. Section 4 presents the results obtained and proposes future research directions. Finally, Section 5 concludes the paper by summarizing its key contributions as well as discussing its limitations and opportunities for further review studies.

2. Methodology

2.1. Typology of extant systematic literature reviews and methods

A literature review represents a specific piece of scientific inquiry, a method by which previous research is collected and synthesized (Snyder, 2019) in order to advance a subject's understanding and outline an agenda for future research (Kumar et al., 2020c). Littell and colleagues (2008, p. 1-2) define systematic literature reviews as "*research that bears on a particular question, using organized, transparent, and replicable procedures at each step in the process*". Paul and Rialp-Criado (2020, p. 2) expand upon this definition, providing an overview of several types of systematic literature reviews, namely *structured reviews* focusing on widely used methods, theories, and constructs (e.g., Ngai et al., 2015; Mishra et al., 2020; Casprini et al., 2020); *hybrid-narratives with a framework for setting future research agendas* (e.g., Dabić et al., 2020); *theory-based reviews* (e.g., Ozturk, 2020); *meta-analysis* (e.g., Fetscherin & Heinrich, 2015); *bibliometric reviews* (e.g., Randhawa et al., 2016); and *reviews seeking model/framework development* (e.g., Paul & Mas, 2019).

Further screening of up-to-date literature reviews by Furrer and colleagues (2020) outlined three prevalent methodologies: *expert-based surveys* (see Davenport et al., 2020), which provide reflections and offer future research agendas but may suffer from author subjectivity bias; *citation studies*, which overcome the weakness of subjectivity as they adopt a quantitative approach which, in turn, lacks the richness of expert surveys (see Kumar et al., 2020b); and *content analysis* (see Dabić et al., 2020), which provides systematic and rich data but incorporates a certain degree of author subjectivity during the coding process.

Prior reviews of AI and marketing have predominantly followed expert-based and citation-based approaches (see Table 1). For example, scholars have previously focused on AI and new technologies (Kumar et al., 2020a), the role of AI within the general business domain (Loureiro et al., 2020), or sub-domains of marketing, such as sales (Syam & Sharma, 2018) and business-to-business (B2B) marketing (Kumar et al., 2020b).

-----Insert Table 1 about here---

In order to expand the research domain of AI and marketing, this study adopts a *content analysis* based *hybrid-narrative systematic review* approach, offering a *framework for setting future research agendas*. The adoption of this approach enables the integration of "the tenets of both bibliometric and structured reviews" (Paul & Rialp-Criado, 2020, p. 2), simultaneously minimizing the authors' subjectivity biases and offering a more objective account of the research domain (Furrer et al., 2020).

The chosen systematic literature review type and the methodological approach selected are operationalized as follows. First, we specified the search criteria and collected the articles. Second, we performed an in-depth analysis of the selected articles and generated the content-based codebook. Third, we performed the MCA analysis and illustrated the AI and marketing research domains' intersection. The findings of the analysis are presented in Section 3. In Figure 1, we present the methodological protocol performed.

---Insert Figure 1 about here---

2.2. The sample of articles and data collection

The data collection began by searching for articles that contained (in their title, abstract, or the authors' keywords) terms such as "marketing" AND "artificial intelligence OR intelligent system(s)", as recommended by Martínez-López and Casillas (2013). The search was performed among Thomson Reuters Social Sciences Citation Index (SSCI), Science Citation Index Expanded

(SSCI) list of journals[1], or those indexed in the Elsevier Scopus database[2] (Paul & Rialp-Criado, 2020). To ensure the validity of the review, we limited our analysis to academic journals that had a peer-review process (Podsakoff et al., 2005) and were written in English. We excluded book chapters, book reviews, conference proceedings, and editorial notes (López-Duarte et al., 2016). Finally, in order to graphically depict the evolution of this research topic, we did not impose any time constraints. This enabled us to map the trajectory of the intersection of marketing and AI. The search criteria at the date of extraction (8th May, 2020) resulted in 164 articles, which, following the recommendations of Graneheim and Lundman (2004), were reviewed by an international team of four members.

The final list includes 164 articles published in academic journals between 1987 and 2020. Increased attention among scholars, as demonstrated by a notable increase in recent published academic articles (see Figure 2), is a testament to the need to map the intellectual structure of the field and facilitate the understanding of this research theme's foundations (Patriotta, 2020; Tranfield et al., 2003).

-----Insert Figure 2 about here---

The advancement of academic interest in this area relies on the journals most frequently publishing articles positioned at the intersection of marketing and AI, such as the *Journal of the Academy of Marketing Science, Industrial Marketing Management, the European Journal of Marketing, and the Journal of Business and Industrial Marketing*, among others (see Table 2). Additionally, Table 2 reveals notable studies published in those journals and outlines that 78.0%

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[1] http://mjl.clarivate.com/publist ssci.pdf
[2] https://www.scopus.com/sources.uri

of publications reviewed in our study were published in journals with an Impact Factor of above 1.0 (2020 impact factor). This is in line with the research of Paul and Rosado-Serrano (2019) and Chatterjee and Sahasranamam (2018), who define influential articles as those published in SSCI indexed journals with an impact factor above 1.0, a necessary condition required in order to shape research fields and provide a baseline for further developments.

-----Insert Table 2 about here---

2.3. The building of the codebook

The protocol for building the codebook (see Figure 1) consisted of identifying the main descriptors within the research field and carrying out the MCA (Dabić et al., 2020; Furrer et al., 2008, 2020). Following the methodological procedure outlined in López-Duarte and colleagues (2016, p. 512), using QDA Miner v.5 and Wordstat v.8 software, this stepwise process consists of "(I) extracting the key content from the articles' titles, abstracts, and keywords; (II) classifying it in order to build a reduced list of the core descriptors; (III) revising the codebook by merging the similar categories in order to obtain a meaningful list of descriptors in terms of content and frequency". The genesis of the initial codebook was based on previous literature reviews conducted within the two respective research fields (Baesens et al., 2009; Davenport et al., 2020; Martínez-López & Casillas, 2013; Kumar et al., 2019) (see Table 1). Building upon the initial classification and categorization, the authors extracted the key content and generated the final codebook, which consisted of 887 terms classified into 21 descriptors. The descriptors were further clustered into six broad themes according to their characteristics: theoretical approaches/frameworks, marketing and AI major research themes and topics, methodologies used, geographical scope, industrial sectors, and levels of research. The entire list of keywords and descriptors is available in the supplementary material.

2.4. The Multiple Correspondence Analysis (MCA)

To map the intersection of the research fields of marketing and AI, we used MCA procedures (Greenacre & Blasius, 2006; Hoffman & Franke, 1986; Hoffman & De Leeuw, 1992). MCA is a quantitative technique characterized by its ability to identify the relationships between dichotomous variables (the occurrence of the defined key content in this study) (Gifi, 1990). A value of “1” was entered if the term appeared and “0” if the term was absent. In line with the goals of this study, the homogeneity analysis by means of alternating least squares (HOMALS) analysis was performed using SPSS (v. 26) software, enabling the illustration of the research field’s intellectual structure on a low-dimensional proximity map. Descriptors were positioned along the two axes (see Figure 3). Accordingly, the proximity of the descriptors corresponded with the common constituent. In the event of a large proportion of the articles involving similar descriptors, descriptors were positioned close to each other and vice-versa (Bendixen, 1995). Furthermore, the closer the position of the descriptor was to the center of the map, the larger the number of articles researching the topic within the field.

3. Findings

The general focus of research on marketing has gradually progressed towards an increasing intersection with research expert systems (Gill, 1995; Steinberg & Plank, 1990) and, more recently, AI (Davenport et al., 2020; Kumar et al., 2020a; Rust, 2020). Accordingly, the findings of our study reveal numerous facets and angles that, through this development, have been somewhat concealed (see Figure 3). The review performed specifically uncovers the outline of a nascent theoretical context, a very large diversity of research themes, and information on the contexts and particular challenges faced in different strands of research within the field.

-----Insert Figure 3 about here---

To illustrate the link between marketing and AI and reveal research opportunities, the initial phase of this study required an understanding of the research domain portrayed in Figure 3, along with its dimension poles (see Table 3) (Hoffman & De Leeuw, 1992). The proportion of variance explained by each pole accounts for 22.21% of the variance. However, this indicator tends to mislead, as the map combines the information of the k variables (21 descriptors) in only two dimensions (Dabić et al., 2020; Furrer et al., 2008; López-Duarte et al., 2016). In agreement with Hair and colleagues (1998), Furrer and colleagues (2008; 2020) noted that variance could have a deceptive effect on the MCA approach and that the overall mean of keywords per article - which should be larger than 1 - is more profound. In our case, it was 1.23.

-----Insert Table 3 about here---

As a result, our analysis identified the dimension of behavioral profiling on the far-left horizontal line. The publications within this category focus on behavioral approaches to segmentation, targeting, and positioning (Belanche et al., 2019; Casabayó et al., 2004; Miralles-Pechuán, 2018; Pitt et al., 2018) while considering ethical concerns that may arise through the implementation of AI (Belk, 2020; Martin & Murphy, 2017). The far-right end of the horizontal dimension demonstrates a specific focus on technological and marketing strategies (Bonnin & Rodriguez, 2019; Gardé, 2018; Li, 2000, 2004; Paschen et al., 2019; Yazici et al., 1994). The upper part of the vertical axis identifies a dimension focused on customer relationships and customer-centricity, while taking into consideration marketing channels and the overall impact of AI on performance (Daskou & Mangina, 2003; Moriuchi, 2019; Payne et al., 2018; Steinhoff et al., 2019), whereas the lower part focuses on technology-oriented approaches, including technological theoretical foundations and macro-level elements of marketing research (e.g., firms, institutions, environment) (Tam et al., 1994; Weber & Schütte, 2019 Wirtz et al., 2018; Zenobia et al., 2009).

In addition to labeling the map's poles, it is also important to acknowledge that the greater the distance between the descriptors in the map, the lesser their association, thus indicating potential research gaps and future research opportunities (López-Duarte et al., 2016). In this way, we outline the theoretical foundations revealed by our content analysis. We present the findings pertaining to the predominant research themes concerning AI and marketing in the following sub-sections. In line with the identified descriptors and their positions within the domains illustrated in Figure 3, these findings serve to establish a foundation for future research directions, as presented in Section 4.[3]

3.1. Theoretical foundations

3.1.1. Behavioral Theories

A primary goal of marketing science is to describe, model, and predict the behavior of consumers towards products. As a result of the emergence of a new type of customer (i.e., an individual that is more informed, demanding, sophisticated, and whose needs are rapidly changing) (Klaus & Zaichkowsky, 2020), and in light of the 'new normal' reality caused by the COVID-19 pandemic, marketers face additional issues when it comes to understanding customer behavior (Sheth, 2020). The importance of the insights unveiled by user data shared on the internet has been of particular interest to marketers in recent years. In particular, further comprehension of

[3] The entire sample of 164 papers was considered when developing insights based on theoretical groundwork, research themes, methodologies (Aguinis et al., 2009), and geographical contexts. However, due to space limitations, we have adopted a parsimonious approach, and we highly encourage readers to further explore the entire list of articles available in the supplementary material.

consumers' digital footprints and their widespread use of web facilities can, along with the use of AI, assist in the design of commercially successful products and services (Kühl et al., 2019). Several studies have acknowledged AI's ability to analyze complex data and identify behavioral patterns and insights, ultimately assisting marketers in making strategic decisions and decreasing the churn rate (Casabayó et al., 2004). In this vein, Liker and Sindi (1997) found that a user acceptance model for expert systems was affected by attitude, perceived usefulness, perceived impact on career, and perceived impact on job security. Similarly, but with regards to consumers rather than marketers, Moriuchi (2019) measured the influence of the perceived ease of use and perceived usefulness over consumers' engagement and loyalty when AI technological enablers, such as voice assistants (VA), were used. Furthermore, Yang and Lee (2019) noted that VA adoption is determined by perceptions of utilitarian and hedonic values and that these are composed of perceived usefulness, perceived enjoyment, portability, automation, content quality, and visual attractiveness. Additionally, Nguyen and Sidorova (2018), building upon self-determination theory, furthered our understanding of human-AI interaction, positioning perceived autonomy, competence, and cognitive effort as antecedents of AI user satisfaction. Therefore, it seems that, in order to adopt an AI-powered device and enhance its usage, potential customers must also perceive a higher hedonic value in addition to the device's practical utility (Belanche et al., 2019).

In recent years, scholars have considered the impact of the "psychology of automation" on AI (Klaus & Zaichkowsky, 2020) in order to reveal the ways in which AI provokes an overconfidence effect among users, caused by biased perceptions and misguidance or discomfort. This suggests that, even though advanced quantitative approaches have been developed, human judgment is still relevant (Coldewey, 2018). In firms, for instance, it is important to guarantee that

AI can be regarded as an ethical problem-solver that requires the commitment of all hierarchical levels within a firm (Amen et al., 2020a; Belk, 2016; 2020). Otherwise, intentions to use AI run the risk of being jeopardized. To embrace AI, all levels within the firm are expected to have an aligned vision when it comes to its utilization. As such, the employment of AI-powered marketing tools should be aligned with the ways in which consumers perceive them, guaranteeing that the development of managerial decision-making is in accordance with the process of understanding customers (Longoni et al., 2019).

3.1.2. Foundations of Customer Relationship Management (CRM)

Customer relationship management (CRM) encompasses the processes and enabling systems supporting a strategy that attempts to create profitable long-term relationships with specific customers. CRM has grown in importance in line with our increasing awareness that customer acquisition is costlier than maintaining existing customers (Ling & Yen, 2001). With this in mind, several outcomes of AI can contribute towards leveraging the enhancement of relationships. Building upon AI’s ability to predict which customers are most likely to respond to marketing campaigns using traditional RFM (recency, frequency, and monetary value) methods with demographic and psychographic variables (Cui et al., 2012), the focus of CRM has been on the use of new technologies and methods (Chatterjee et al., 2019). Thus, recent advancements in technology amplify CRM’s potential through the effective use of collected data and prominent interactivity in a way that fosters customer relationships (Bock et al., 2020; Kaplan & Haenlein, 2019) and ultimately enables customer-centricity (Latinovic & Chatterjee, 2019), co-creation, and co-production (Ranjan & Read, 2016).

In line with the evolution of AI and marketers’ growing aspirations towards customer-centricity (Sheth et al., 2000; Wang et al., 2020), CRM has been viewed as a way by which to implement a customer-facing approach across the entire organization. Therefore, AI plays a crucial role in transforming data into marketing insights (Shah et al., 2006). For example, AI includes text and voice-driven conversational agents (De Keyser et al., 2019) that exhibit aspects of human intelligence (Huang & Rust, 2018; Rust, 2020). This state-of-the-art technology includes perception, reasoning, and actuation, combined in the form of algorithms, which lead to improved customer service and performance (Belanche et al., 2020). Accordingly, in order to better explain the value of AI within the CRM range of actuation, it is important to acknowledge two spectrums: service encounter characteristics and customer features that must be considered permanent adjusters of conversational agents (Bock et al., 2020).

When considering service encounters, the notion of the customer journey has particular relevance. This, according to D'Arco and colleagues (2019), is useful when trying to understand the ways in which AI can assist in different areas (ranging from customer profiling to the management of CRM initiatives), ultimately contributing to the improvement of the customer journey across all touchpoints. Consequently, Ngai and colleagues (2009) and, recently, Paschen and colleagues (2020) acknowledged that advanced marketing intelligent systems could equally benefit different sales funnel stages, seemingly increasing customer lifetime value through the promotion of loyalty programs and one-to-one marketing initiatives.

When it comes to the customer features that must be considered when managing relationships with clients and considering the bots' permanent adaptation, particular attention is given to constant updating of the data collected. According to Heaven (2020), during the COVID-19 pandemic, an AI-powered credit card fraud detection system was not able to cope with what seemed to be erratic consumer behavior. During the initial period of the recent global pandemic, some consumers were demonstrating unusual consumption activities towards certain products and services (e.g., hand sanitizer, personal protective equipment) that did not align with their expected behavior, according to extant algorithms (Pantano et al., 2020). Consequently, as customer behavior changes, AI-powered marketing systems need to change and adapt, learning from new events and circumstances (Rust, 2020).

3.1.3. Knowledge-Based View

Building on the resource-based view, which conceptualizes firms as a collection of resources (Penrose, 1959), the knowledge-based view (KBV) treats knowledge as a distinctively unique resource (Kogut & Zander, 1992), which can be either explicit (i.e., can be written down and transferred easily through systematic language) or tacit (i.e., more difficult to decode and describe) (Polanyi, 1958). Within the KBV, the concept of knowledge integration has attracted significant attention, with several authors seeking to distinguish between knowledge integration processes and knowledge integration outcomes (Kearns & Shabherwal, 2006). The former refers to actions through which individuals apply or share specific knowledge or combine it to develop new knowledge, while the latter refers to the outcomes of that knowledge being shared, applied, or combined with other forms of knowledge in order to create new knowledge (Grant, 1996). As a result, researchers have developed an approach to *handle* the knowledge that enabled the creation of the *"means"* to solve problems. This advancement gave rise to 'knowledge-intensive computer programs' (i.e., expert systems) (Harmon & King, 1985). Technologically, knowledge management systems (KMS) have attracted scholarly attention as they have evolved from concepts such as executive information systems, decision support systems, and expert support systems (Nevo & Chan, 2007).

From a marketing perspective, considering KMS as a building block of AI offers opportunities that facilitate knowledge integration (Paschen et al., 2019). By imitating humans in terms of the ways they think and act through various technologies, AI can ‘learn’ and improve itself progressively by updating its knowledge base and capabilities (Coldewey, 2018). The applications of AI are generally deemed more suitable for the acquisition of explicit knowledge - knowledge that can be specified verbally or in writing, such as computer programs, patents, drawings, concepts, or formulas (Hau & Evangelista, 2007). On the other hand, tacit knowledge is obtained through experiential learning, insight, intuition, senses, or implicit rules of thumb (Leonard & Sensiper, 1998; Nonaka & von Krogh, 2009). These attributes constitute a major difference in the learning processes of the two forms of knowledge. While explicit knowledge can be transferred in various ways and can migrate or move around the world in seconds, the transfer of tacit or embedded knowledge is very slow (Badaracco, 1991) and requires extended social contact (Nonaka et al., 2000). For this reason, it has been argued that the intrinsic characteristics of tacit knowledge might represent a significant obstacle when it comes to its implementation within the context of AI technology (Fowler, 2000).

The value of AI applications, however, has been demonstrated through the acquisition of customer knowledge, enabling firms to map customer’s journeys and create meaningful content for such journeys through marketing automation in both B2B and business to customer (B2C) environments (Mero et al., 2020; Syam & Sharma, 2018). Through predictive models, AI can also cultivate marketing efficiency by evaluating prospective customers on their propensity to buy and identifying high-quality leads (Järvinen & Taiminen, 2016). Additional applications in the marketing domain include knowledge-based technologies, such as sentic computing, which relies on the accumulated application of common-sense computing and the psychology of emotions in order to infer the conceptual and affective information associated with natural language (Poria et al., 2014), or the gender classification of text based on natural language processing (Mukherjee &

Bala, 2016). In short, the use of the KBV in the context of marketing and AI highlights the important role of automation in the creation, codification, transfer, and application of knowledge, enabling a more holistic understanding of consumer needs and behaviors across devices, platforms, and products (Kumar et al., 2019).

3.1.4. Network Theory

Research on networks has become central to several disciplines, including marketing, due to its ability to explain a variety of social phenomena and its intrinsic cross-disciplinary nature. Networks are built upon relational data and can be defined as a set of actors (e.g., individuals or groups) with some pattern between them in terms of relationships or interactions (Oliveira & Gama, 2012). Borgatti and colleagues (2009) noted that one of the central tenets of network theory is that a node's position in a network determines the opportunities and constraints that it encounters, playing an important role in its outcomes. One of the most studied characteristics of networks is centrality, which helps to identify the structural importance or prominence of a node in a network through several indicators, such as degree, betweenness, closeness, and eigenvector centrality (Freeman, 1977).

In marketing, networks have been studied in terms of the ways in which customer networks affect word-of-mouth effectiveness (Zhang et al., 2020), service purchase decisions (Bansal & Voyer, 2000), customer equity (Chae & Ko, 2016), and the diffusion of products and services across borders (Elo et al., 2020). Of particular interest has been the identification within such networks of influencers, i.e., individuals that are well-connected and have a substantial influence on others (Keller & Berry, 2003). As central individuals often play an important role in spreading information (Jalili & Perk, 2017), centrality measures have emerged as powerful predictors of a person's influence in a network and have been shown to be useful in a variety of decision support system applications. The PageRank algorithm, for example, which is the fundamental search engine mechanism of Google, uses the topology of the web as an indicator of the value attached to any page (Brin & Page, 1998). Using a number of computational experiments on artificial and real networks in call data from a telecom company, Kiss and Bichler (2008) observed a significant increase in message diffusion when using influencers. Several studies have measured social influence by counting how much information related to a topic can be diffused in a network. Focusing on viral marketing, researchers have used social media platforms, such as Twitter, to measure a user's influence (see Riquelme & González-Cantergiani, 2016). An interesting extension of this stream of research is represented by the notion that individuals who want to emerge as influencers compete in order to do so, a concept known as competitive influence maximization. Using the Competitive Influence Improvement (CI2) algorithm, for example, it is possible to identify the minimum number of influential nodes within an influencer's networks (Bozorgi et al., 2017). In short, the use of networks in marketing and AI highlights the increasing role of AI applications, such as algorithms, in identifying patterns of influence that affect both consumer choices and firms' product offerings.

3.2. Major research themes and topics

While the twentieth century observed a lack of application of intelligent systems in marketing (Gill, 1995), recent years have been characterized by rapid advancements in information technology (Naudé, 2020). Currently, AI is being applied in various contexts, from automated fact-checking in journalism to powering chatbots that interact with customers on e-commerce websites. To identify the reference points of AI and marketing, we utilized systematic search methods using multiple sources as an initial foundation. Building upon the results of content analysis, combined with the HOMALS technique (shown in Figure 3), we present the four major research themes identified in line with the technological advancement and application of AI in marketing while taking into consideration potential threats to privacy and the increased vulnerability of users (Letheren et al., 2020).

Theme 1: Marketing Channels

Marketing channels are meant to bridge the gap between producers and consumers, representing a crucial link in the buyer-seller exchange. Given that the purpose of marketing channels is to ensure efficiency, a large body of literature on marketing channels acknowledges the endless opportunities for improvement in this area through AI technologies and applications (e.g., robots, voice assistance devices, etc.) (Bock et al., 2020; Wirtz et al., 2018). Essentially, AI's unparalleled ability to gather and interpret existing data in a correct way, learn from it, and use it in an intelligent manner (Kaplan & Haenlein, 2019) is dependent upon AI technological enablers (e.g., machine learning, deep learning, and neural networks, among others)[4]. Recent technological developments have influenced marketing channels and have attracted the attention of both scholars and practitioners (Moriuchi, 2019; Poria et al., 2014). Retailers such as North Face, Amazon, 1-800-Flowers.com, and many others are already incorporating the most recently updated innovations based on AI from social media to retailing analytics (i.e., Pepper Robot, Conversica Sales Agent, IBM Watson Cognitive Computing) (Angus & Westbrook, 2019; Sjödin et al., 2018). The reasoning behind these investments lies in the firms' assurance that the recognition of customer demographics and psychographics will assist marketers in customer profiling and allow

[4] The authors recommend readers to see Bock and colleagues (2020) as well as SAS (2019) for more information regarding AI technological enablers.

them to better predict consumers' choices, either in terms of prospection and comparison, but mainly in terms of purchase and the physical distribution of goods.

The COVID-19 pandemic has increased demand for marketing channel enhancements, as customers are currently confined to their homes and are less able to access physical stores (Pantano et al., 2020). Given this new reality, as well as the ongoing changes in consumers' preferences with regards to searching and analyzing through multiple channels (Silva et al., 2018; 2020), rather than interacting with conventional sales assistants (Grewal et al., 2020), AI solutions are being recognized as additional and, to some extent, alternative marketing assistants when it comes to understanding customers (De Cicco et al., 2020; Wirth, 2018). Casabayó and colleagues (2004) acknowledged that AI's capabilities, in terms of language processing, image recognition, and the overall leverage of powerful tools and algorithms, can access data from both internal and external sources. These characteristics provide no-cost on-premise technology and represent the basis for better dynamic attribution and online targeting (Gardé, 2018). Hence, AI, in using semantic recognition, generates databases from which marketers can extract information and learn about customers (Adi et al., 2020). This approach offers resourceful insights (Paschen et al., 2020; Wirtz et al., 2018) in the 'new normal' landscape triggered by the COVID-19 pandemic, as demonstrated by unusual customer behavior and business actions.

Theme 2: Marketing Strategy

Intelligent systems for marketing strategies are ultimately changing the way businesses are conceived (Pantano et al., 2020). In this sense, AI has assisted in establishing new paradoxes in strategy, such as recognizing the advantages of massification alongside those of customization (Du et al., 2003), the association of the pros of luxury/premium brands with those of the mass market

(Kumar et al., 2020c; Paul, 2019), as well as the combination of niche markets with the benefits of the large market through e-commerce (Meiseberg, 2016).

The continuous evolution of AI technology affects the future of marketing strategies (Rust, 2020). For example, some of the most relevant problems, such as the alignment of strategic orientation with market potential (Griffith et al., 2012), are solved nowadays using AI solutions. In this way, implementers of AI-based marketing solutions have noted improvements in business model decisions (Valter et al., 2018), new product development (Chan & Ip, 2011), communication (Paschen, 2019), pricing (Calvano et al., 2019), sales management (Flaherty et al., 2018), advertising (Kietzmann et al., 2018), and personalized mobile marketing strategies (Tong et al., 2020). Additionally, in service industries, different types of AI (i.e., mechanical, analytical, and intuitive) are being recognized as sources of innovation and enablers of higher productivity, causing a redefinition of the workplace and task allocation (Huang & Rust, 2018). Hence, for service tasks that are based on routines and simple transactions involving more standardization (e.g., shipping, delivery, and payment), a cost leadership advantage should be pursued through a more mechanical type of AI. For service tasks that rely on learning with data (e.g., the identification of new markets or services, personalization), a quality leadership advantage should be pursued through a more analytical type of AI. For tasks that rely on experiential learning (e.g., engagement with customers), a relationship advantage should be pursued through a more intuitive type of AI. Altogether, the different types of AI can gradually enhance service task performance depending on the offering, strategy, and processes (Huang & Rust, 2018; 2020).

Considering the changes made to business models, sales processes, customer service options, and marketing information systems (Donthu & Gustafsson, 2020), it is important to acknowledge ethical problems and data protection issues (Etzioni & Etzioni, 2017; Ameen et al., 2020a). Accordingly, data collection through speech recognition, in which the clients' tone of voice when communicating with voice bots, along with other data used to improve marketing strategies, requires alignment with the General Data Protection Regulation and approval of the client (Butterworth, 2018). Hence, in order to reduce consumers' skepticism and avoid speciesism toward AI (Schmitt, 2020), practitioners are reminded of ethical codes (Stone et al., 2020) and the importance of data protection (Kolbjørnsrud et al., 2017).

Theme 3: Performance

Scholarly literature on AI and marketing examines performance under two separate lenses. The first lens focuses on how AI tools and techniques score in terms of performance with respect to more conventional tools and methods. Such a comparison, in terms of performance, is particularly valuable in solving the higher accuracy versus higher cost trade-off typically associated with these methods. AI, through its technological enablers (Bock et al., 2020), which are considered a prerequisite for its development, performs better in its ability to make predictions as it can accommodate highly nonlinear and complex relationships between inputs and outputs (Russell & Norvig, 2016; Syam & Sharma, 2018).

The second lens treats performance as an outcome variable. It focuses on how and if AI can contribute to performance in terms of competitive advantage efficiency, sales prevision, sales performance, and value creation for customers, among others. Companies can benefit from AI by translating big data into information and knowledge, allowing them to develop more effective marketing and sales strategies, which often translate into a sustainable competitive advantage (Paschen et al., 2020). By using decision support systems, marketers enhance the efficiency of marketing programs by fully utilizing all available databases (Kim & Street, 2004) and estimating the net customer lifetime value from customers' purchasing behaviors (Chan & Ip, 2011). In addition, AI applications have been used to support customer value creation in many instances, for example, in the insurance industry (Riikkinen et al., 2018). In the hospitality industry, a study on how the Hyatt Hotels Group used AI to improve cross- and up-selling to customers found that room revenues increased up to 60% through these techniques (Diaz, 2017). By using AI-powered marketing tools, companies can also predict what customers may want to buy, thus improving their sales funnel. More recently, Syam and Sharma (2018), as well as Davenport and colleagues (2020), noted that AI affects companies' sales processes and, consequently, their sales performance. Besides current sales performance, firms expect to benefit from AI regarding anticipation of trends and changes in demand (Pantano et al., 2020). The calculation and prediction of future trends, accomplished through forecasting, can be facilitated by AI through the development of accurate tools, such as the Adaptive Neuro-Fuzzy Inference System and the Modular Genetic-Fuzzy Forecasting System (Hadavandi et al., 2011; Shahrabi et al., 2013). Other examples of AI techniques in the field of sales forecasting include Support Vector Machines and Neural Networks (e.g., Carbonneau et al., 2008).

Theme 4: Segmentation, Targeting, and Positioning (STP)

Recent developments in segmentation, targeting, and positioning (STP) research have primarily addressed problems related to dealing with the customer base of a firm through variables such as demographics (Belanche et al., 2019), psychographics (Poria et al., 2014), geographic considerations (Wu et al., 2015), and behavioral segmentation (Belk, 2016), which seem to be the fields in which AI provides vital assistance. Accordingly, dealing with client acquisition (Quijano-Sanchez & Liberatore, 2017), customers' preferences and consequent clustering (Pitt et al., 2018; Shahrabi et al., 2013), and obtaining sales efficiency in their targeting (Flaherty et al., 2018;

Cherviakova & Cherviakova, 2018) are issues which have received significant attention among marketing scholars and practitioners (Rust et al., 2020).

The advances in this field allow different segments and generational cohorts to be better served (Lei & Moon, 2015), enabling the anticipation of customer profile shifts as well as post-demographic consumption (Pitt et al., 2018). Arising from the eager attempt to implement the "shipping-then-shopping" model (Davenport et al., 2020), positioning the right proposal in the right segment has been a concern of some researchers (Wu et al., 2015; Lei & Moon, 2015). Research conducted by Chica and colleagues (2016) enhanced brand positioning with the assistance of mechanisms involving complex choices that permitted the modeling and evaluation of brand decisions in an intelligent way. One of the best examples of the power of AI can be seen in the correct recommendations that Google's algorithms can produce, based on millions of unconsciously made incorrect entries (Makridakis, 2017).

Within this research stream, a large body of literature has focused on neural networks and artificial neural networks (ANN). ANN represent a type of AI computing based on a nonlinear, nonparametric regression model that mimics the structure and function of the brain (Ha et al., 2005). The main advantage of neural networks is that they can estimate very complex relationships (D'Haen & Van den Poel, 2013). Hence, neural networks have been seen to be more accurate in classifying potential customers into groups for market segmentation in comparison to discriminant analysis and logistic regression (Fish et al., 1995) and can outperform multinomial logit in terms of brand share estimation (Fish et al., 2004). The predictive power of neural networks has been used, for instance, to predict customer churn in the mobile telecommunications industry, using subscriber contractual information and call pattern changes (Wei & Chiu, 2002). Additional examples of studies using neural networks include Li (2000), who developed an ANN to analyze and forecast market growth, and D’Haen and Van den Poel (2013), who created an analytical model with three phases using diverse methods, among which decision trees and neural networks were used to facilitate customer acquisition in B2B environments.

4. Discussion and directions for future research

Academic focus on AI in the field of marketing can be traced back to the 1980s, with studies considering AI’s applications and tools as decision support systems in forecasting (Collins et al., 1987) and sales (Steinberg & Plank, 1987), among others. Our review of 164 papers advances scholars’ and practitioners’ understanding of this promising domain by demonstrating the ways in which AI assists marketers in predicting customer behavior, customer value creation, business process automation, and productivity, among other factors (Davenport et al., 2020; Chan & Ip, 2011; Kumar et al., 2020a). Hence, building upon the findings presented and our review of extant studies positioned at the intersection of AI and marketing, we outline future research avenues and provide potential implications for practitioners.

4.1. Future research avenues regarding theory

The evolution of AI’s applicability, from Simon’s (1985) expert systems to the notion of Society 5.0 (Salgues, 2018), shows that the future lies in the unique features of AI and intelligent systems’ enrichment of marketing and its development of advanced empirical and theoretical models. Despite the benefits of AI and the technological progress made, limited acceptance of AI from a user perspective has been a core challenge over the past few decades. With this in mind, recent studies predict that the acceptance process will prove to be further complicated as AI applications expand into domains of higher intelligence (Chi et al., 2020) and ethical concerns arise (Dignum; 2018; Jobin et al., 2019). To better understand how and why certain technologies, such as AI, are accepted or rejected, future studies could explore the *acceptance of AI technology* through the lens of theories grounded in psychology. Among them, a core theoretical framework is the Technology Acceptance Model (TAM) (Davis, 1989), along with its subsequent extensions, including the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Value-based Adoption Model (VAM) (Kim et al., 2007; Venkatesh et al., 2003).

When it comes to AI user adoption (Seranmadevi & Kumar, 2019), technology acceptance theories offer interesting avenues for further theoretical and empirical development. Given the slow and limited acceptance of AI by users (Chi et al., 2020), a natural avenue for future research is the *adoption and usage of AI technology and applications*, with a particular focus on the individual- or user-level characteristics that could affect the acceptance, use, and adoption of AI technology, in line with ethical concerns regarding privacy and safety. Cognitive and emotional aspects could, for instance, predict perceived usefulness and perceived ease of use of AI or moderate the relationship between the intention to use AI and the actual use of AI, in line with the importance of data protection and ethics (see Table 4 for an overview of the proposed research questions).

The cognitive aspects required when interacting with a specific type of technology, such as the level of attention, i.e., the general distribution of mental activity to the tasks being performed by the individual (Moates & Schumacher, 1980), could potentially affect a user's attitude towards a specific technology (Luna et al., 2002). However, less is known about the ways in which degrees of attention might affect actual usage or adoption intentions in the context of AI technology when it comes to threats to privacy and data protection. Future research could incorporate more reason-based and emotional factors in order to determine the role of user acceptance for AI. For instance, hedonic motivations have been considered major determinants of AI service usage (Lin et al., 2019) as customers interact with these services for fun and out of curiosity (Kuo et al., 2017) rather than for their usefulness. A similar conclusion was also reached by Sohn and Kwon (2020), who stated that customers may value enjoyment over practical use because the diffusion of AI-based products is moving towards the early adoption stage, in which individuals are generally curious about new technology.

The demographic profile of users in relation to their tendency to adopt or use AI is an additional research stream in itself, deserving further exploration. Previous studies have focused on two demographics, namely, age and gender (De Cicco et al., 2020). With respect to age, several studies have reached the conclusion that younger users have more positive attitudes towards AI when compared to older people, particularly in the context of robotic services (Onorato, 2018). For gender, previous studies tend to agree that men seem to express fewer negative perceptions than women when it comes to AI technology in contexts such as children's education (Zawacki-Richter et al., 2019) or hotel services (Ivanov & Webster, 2018). Similar conclusions have also been reached by Davenport and colleagues (2020), who suggest that women are less likely than men to adopt AI. The relationship between AI and gender has also been explored in terms of the gender profiling of online content. Capturing gender differences by using AI-based applications has been deemed relevant to companies as it allows for the improvement of several commercial domains, including product development and target advertisement (Mukherjee & Bala, 2017). After exploring the ways in which demographic characteristics can impact the adoption and use of AI, it would be interesting to examine whether gender traits (e.g., voice, appearance, etc.) of AI-based applications and technology are more or less likely to influence adoption based on similarities or dissimilarities between the user's gender and the gender traits attributed to AI.

An additional area that deserves further exploration is the relationship between culture and AI. While previous studies have argued for the importance of incorporating cultural differences in models dealing with the acceptance of technology in general (Marangunic & Granic, 2015) and of AI more specifically (Belanche et al., 2020), there is a limited amount of research on the ways in which culture influences the adoption and use of AI. Such studies could be conducted at a national level or across cultural dimensions, exploring individualism and uncertainty avoidance (Belanche et al., 2020) across nations and examining whether they lead to positive or negative attitudes towards AI technology.

Another interesting pathway for future development, incorporating some of the considerations mentioned above, is represented by the simultaneous focus on three elements affecting customers' acceptance of AI technology, namely factional, relational, and socio-emotional elements (Wirtz et al., 2018). While factional elements (e.g., perceived ease of use and perceived usefulness) are well-represented in technology acceptance theories, more attention could be paid to relational elements, such as trust, and socio-emotional elements, such as perceived humanness. Practice-oriented research suggests that when consumers express their feelings towards AI, they often express concern, skepticism, and suspicion, demonstrating consumers' reluctance to trust the technology (Davenport, 2018). It would be interesting to examine the correlation between trust (a relational element) and perceived humanness (a socio-emotional element) with respect to AI-powered devices. Results from research on anthropomorphic AI devices and consumers' attitudes towards them have yielded mixed results (e.g., Lin et al., 2019; van Pinxteren et al., 2019). Future studies might explore how the relationship between perceived humanness and the acceptance of AI technology is mediated or moderated by trust. All in all, technology acceptance theories serve as valuable theoretical frameworks for future studies in this field, offering exciting possibilities for building a stronger theoretical foundation for future empirical research in this domain.

4.2. Future research avenues regarding Marketing AI characteristics

The spectrum of benefits enabled by the intersection of AI and marketing is developing intensely and rapidly. In light of the 'new normal' landscape caused by the COVID-19 pandemic and the necessity to self-isolate and depend on technology more than usual (Donthu & Gustafsson, 2020), AI-powered marketing tools are expected to play a central role in our future understanding of consumer's attitudes, beliefs, and behaviors. In fact, even before the pandemic, AI had demonstrated its ability to assist in shopping processes and enhance customer experience (Ameen et al., 2020b; Gacanic & Wagner, 2019). Accordingly, AI-powered marketing tools facilitate easy access to information, assistance in the comparison process, accelerated checkout, and the ultimate growth of overall marketing performance (Martínez-López & Casillas, 2013). Despite these benefits, concerns over ethical issues (e.g., transparency, justice, fairness, and privacy), data protection, and employment opportunities (Makarius et al., 2020) remain some of the major drawbacks of AI technologies. As such, the promising nature of AI may depend on understanding its challenges and its opportunities. One of the major challenges lies in managerial abilities when it comes to comprehending the benefits of new technology and its subsequent contributions to product and service improvements. For businesses, the adoption of AI substantially changes the ways that both marketing strategies and customer behaviors are regarded (Davenport et al., 2020).

In this line, as AI has shifted the paradigm from a rule-based expert systems' approach to a data-driven approach, the implementation of AI within organizations seems to undermine inherited methods of skill development and training (Huang & Rust, 2020). Hence, further investigation regarding the *revolution of the labor market and marketers' competences* is needed, particularly when it comes to soft and hard skills. Building upon the suggestion of Davenport and colleagues (2020) and Huang and Rust (2020) that, depending on the nature of the task, AI is either replacing or augmenting marketers' activities, further investigation is needed into the adoption of a holistic approach that pushes firms to have a different conception of resources and workplace.

Additionally, the path towards the concretization of digital transformation (Rogers, 2016) and the paradigm of Industry 4.0 seem to be dependent on institutional support. Therefore, research on the *role of institutions* at local, national, and international levels could be considered a fruitful avenue for future research through the exploration, for example, of the extent to which public policies and initiatives that promote AI without harming consumers' interests are effective in encouraging the adoption of AI, both by organizations and by individuals.

AI's application in marketing enables the evolution of STP by enhancing the understanding of consumers' needs and wants. Accordingly, tech-savvy companies trace and use digital footprints (i.e., Amazon's "anticipatory" shipping) and comprehend consumers more than ever before. These developments, as anticipated by Kotler and colleagues (2016), have affected the transfer from "what is shopped is shipped" to another possibility, in which shipping is an antecedent of shopping. Additionally, mechanisms such as emotion-sensing technology and emotionally intelligent machines, materialized in devices (i.e., Walmart's emotion-sensing internet-connected shopping cart), truly favor the customer experience. However, all of these advancements come with ethical concerns. Therefore, promoting a win-win-win situation for all involved - individuals, firms, and all other stakeholders - remains questionable due to ethical concerns and represents an opportunity for future research.

A firm's ability to adopt AI marketing advantages in content creation and communication will ultimately exponentiate inbound marketing (Lusch & Vargo, 2009). The opportunity to understand whether or not overwhelming messages could be avoided by targeting the right people with the most efficient media and message types would be another fruitful avenue for future research. Finally, the possibility promoted by AI applications in terms of co-creating (Buhalis & Sinarta, 2019), customizing and personalizing solutions, developing simultaneously massified and customized proposals with several online possibilities of configuration, gives rise to the idea that on-demand solutions are the future, that consumers are unique, and that their needs should be inspirational. This technological alteration has enabled the 'everyone's an expert' era, in which consumers want everything, anywhere, at a good quality, at a fair price, in a differentiated way, and right now. Understanding how managers might cope with such an array of strains represents the next challenge for researchers.

4.3. Future research avenues regarding context and methodology

This study found that the vast majority of research at the intersection of marketing and AI has focused on market contexts such as Europe (Baesens et al., 2004; Casabayó et al., 2004; Kühl et al., 2019), North America (Belanche et al., 2019; Moriuchi, 2019), and Asia (Chopra, 2019; Seranmadevi & Kumar, 2019; Wang et al., 2020). Given the nascent nature of the research field under study, future research could examine the development of AI technology in countries located in the southern hemisphere, taking into consideration the research avenues proposed in Table 4. Moreover, a multi-country approach could present a promising research avenue, particularly considering international differences in *ethical standards and institutional and technical developments*. Furthermore, from a customer perspective, further insights into multi-country and multi-cultural contexts would prove useful, as shown in a study conducted by Belanche and colleagues (2019), who compared Portugal, the UK, and the US. Their study indicated that the influence of subjective norms on the use of AI-powered devices transcends national borders and is much stronger in the UK and the US compared to Portugal, where perceived usefulness was considered much lower.

Overall, the findings of this review indicate that the marketing and AI research field is still in a nascent stage in which many areas remain unexplored. In this regard, the adoption of a multi-level methodological exploratory approach (Jones et al., 2016) promises to further increase our understanding of the role of AI in marketing. Additionally, the vast majority of studies are conceptual studies, demonstrating a need for more direct and indirect observations of AI in marketing that could, for example, test conceptual findings in underexplored sets of individuals, such as digital natives and digital immigrants.

4.4. Future research avenues regarding marketing AI and the COVID-19 pandemic

The impact of AI on marketing cannot yet be quantified in the ‘new normal’ reality caused by the COVID-19 pandemic (Naudé, 2020) as it is characterized by erratic customer behavior (giving rise to noisy and outlying data) and discrepant institutional data privacy regulations (Ameen et al., 2020a). Given that this situation is unlikely to change in the short term, AI-powered marketing tools will depend more on rigorous human-AI interaction (Coldewey, 2018). Thus, given marketers’ need to innovate and adapt to the new reality (Wang et al., 2020), future research is needed on the ways in which marketers can understand and anticipate customers’ behavior and businesses’ actions through AI. As AI is dependent on data, the following questions should be tackled by future researchers: 1) To what extent are marketers willing to gather and share data - both existing and new - in order to inform new AI marketing models? 2) Has the COVID-19 pandemic changed marketers’ approaches to data protection? And if so, how? 3) In light of the COVID-19 pandemic, what role will AI-powered marketing tools play in understanding consumers’ attitudes, beliefs, and behaviors?

Bearing in mind that pandemics and other catastrophes have a tendency to repeatedly affect society (Donthu & Gustafsson, 2020), learning from the consequences of the COVID-19 pandemic could be of crucial value to the long-term reduction of the effects of disasters. As our society is still in the middle of the pandemic and long-term effects are still unknown, marketing researchers and practitioners have the opportunity to evaluate current effects and maximize preparedness for the upcoming period. Under these circumstances, delivering customer convenience and building trust are both significant challenges. At the same time, a number of online businesses in retail and education, among others, were able to adapt quickly and develop new offerings based on AI-powered applications. The COVID-19 outbreak accelerated the implementation of AI's application in marketing (e.g., chatbots, virtual assistants), gradually replacing human-to-human contact. The future of marketing thus truly depends on digital savviness (Sheth, 2020) and state-of-the-art technologies (Rust, 2020), with AI acting as a cornerstone of marketing development.

---Insert Table 4 about here---

4.5. Implications for practice

With the upheaval of information technology, marketers' skills, such as creativity and content creation, and competencies, such as data analysis and reporting skills, have experienced significant changes (Davenport & Ronanki, 2018). With the assistance of AI, marketers are tapping into the profound knowledge of clients' needs, enabling them to perform effective data analysis and organize their activities towards customer-centricity. As such, the adoption of AI in marketing has revolutionized the job requirements of marketers and their overall labor market in terms of skills (Huang & Rust, 2020). However, it seems to free up offices and workstations, allowing work to be conducted remotely (Makarius et al., 2020).

Building upon the labor market revolution, marketers' competencies are expected to evolve in order to remain competitive as they cope with the unprecedented crisis evoked by the COVID-19 pandemic. Intelligent marketing systems are also likely to require constant updates given the unprecedented changes in the environment and due to the massive amounts of new data made available, for instance, through geo-referencing systems used in mobile phones (Ameen et al., 2020a) or complaints verbalized in voice assistance interactions. Different sources of information should include social media, reports by data brokers, digital key performance indicators, and track records of sales, among others, in order to provide personalized recommendations. Sales processes are also likely to change, as AI agents can better monitor conversations in real-time, interpret a client's tone of voice, and scrutinize unsolved situations that may require immediate intervention. This may require different levels of intervention in terms of the information provided, the degree of involvement proposed, the products and services offered, projected levels of compensation, and planned alternatives. Therefore, marketers must be aware that business models will experience disruption and that these changes should be considered with a forward-thinking approach. For instance, driverless cars can produce dramatic changes when it comes to insurance, carmakers, other equipment manufacturers, and even real estate businesses (Davenport et al., 2020) due to their specificities and the consequent time-saving convenience promoted. Therefore, managers are advised to think ahead and, above all, promote knowledge acquisition in their teams.

Overall, marketing strategies, such as advertising and communication, require closer attention from managers in order to remain aligned with changes in consumer decision-making processes, perceptions of time, and confidence triggered by AI (Lemon & Verhoef, 2016). While this new paradigm might appear to be far from being put into practice, global spending on smart home related hardware, services, and installation fees is expected to reach $143 billion per year by 2023, by which point 274 million homes worldwide are expected to have at least one type of smart system installed (Ablondi, 2018). Similarly, a study of Cap Gemini, based on a survey of 5000 consumers, found that the majority would rather follow the advice of an AI-based technology than spend time on a website (Sengupta, 2018). This challenges the very concept of conventional online convenience (Duarte et al., 2018), demonstrating that consumers are more and more inclined to believe that AI-based technology will make the “best decision” for them, as they can filter content according to a user’s profile, based on their track record of purchases and preferences. On these grounds, marketers should consider AI mechanisms as a hub facilitating the capturing, coding, retrieval, and sharing of knowledge. Health issues caused by the COVID-19 pandemic have accelerated the adoption of e-commerce by five years (Haller et al., 2020), with an expected decline in department stores of around 60% and a projected increase of 20% in e-commerce, which is in line with recent research on the phenomenon conducted by Stewart (2020). Thus, given that AI-powered marketing tools can improve the customer experience, driving online sales and, ultimately, creating value for all those involved (Barnes, 2020), they represent one of the fields that may benefit from the pandemic.

5. Conclusion

Research positioned at the intersection of AI and marketing has flourished in recent times. Our review of the academic contributions on this subject across more than 30 years indicates a spike in the number of papers published from 2017 onwards. This academic interest has been accompanied by an equal increase in the attention paid to AI applications by companies such as Google, Spotify, and Under Armor, to name a few. Hence, the knowledge accumulated on AI and marketing offers the opportunity for the systematization and assessment of existing contributions. Therefore, the purpose of this study was to examine research on AI and marketing in order to provide an extensive and holistic review of the existing literature on this topic. Using content analysis, combined with HOMALS statistical procedure, we reviewed relevant literature published between 1987 and 2020. Based on the analysis of these works, this study offers the following contributions.

Firstly, the literature review provides an introduction to the existing literature on AI and marketing that might appeal to researchers, particularly those working in the domain of AI wishing to further explore its application to marketing and vice-versa, introducing them to major publication resources. Secondly, the content analysis reveals five major theoretical dimensions employed by studies in AI and marketing. These dimensions, also presented in the proposed visual map, are related to behavioral theories, CRM, KBV, network theory, and technology-related theoretical foundations. Additionally, our analysis identifies several research themes, namely, the application of AI in marketing, technological advancement, ethics, marketing channels, marketing strategy, performance, and STP. This categorization provides a more granular view of scholarly work on AI and marketing. Thirdly, unlike previous research on AI and marketing, which can usually be classified as structured reviews adopting either expert-based or citation-based methodological approaches, our work adopts a hybrid-narrative approach with a framework for setting a future research agenda by implementing content analysis combined with HOMALS techniques. To our knowledge, this is the first study to adopt this approach when studying the relationship between AI and marketing. Therefore, our paper complements previous expert-based reviews – by offering a more objective account of the development of AI and marketing – and citation analyses – by offering a deeper discussion of the underlying themes and theoretical approaches to the study of AI and marketing. Finally, building upon the literature review performed, we propose research themes that could represent fruitful avenues for further research linked to the adoption and use of AI technology and its applications, the acceptance of AI technology, the revolution of the labor market and marketers competences, the role of institutional support, the importance of data protection and ethics, and the recent COVID-19 outbreak, which will pose additional technological and behavioral challenges. A set of 21 descriptors, along with keywords, are provided in the supplementary material, enabling the replicability of this study.

As with most studies, this research has its limitations. While we see value in the approach undertaken in this study, as it does not impose specific time or subject constraints, limitations can be seen, firstly, in our methodology. The methodological approach employed in this study is subject to a certain degree of author subjectivity by virtue of the process of developing the codebook (Furrer et al., 2020). Secondly, the search query performed using an 'umbrella approach', while having the merit of providing an in-depth overview of studies at the intersection between marketing and AI, it does not focus on any specific sub-field of marketing and AI (e.g., AI and neuromarketing), offering the opportunity for researchers interested in specific sub-fields to perform additional review studies depending on their topics of interest in AI. Therefore, future studies could build upon the work of this review by conducting a more focused analysis of specific areas and sub-fields of marketing (e.g., retail marketing, direct marketing, and social media marketing, among others) and AI. Third, while the inclusion of research from peer-reviewed journals is common practice in literature reviews, relevant research published in books or conference proceedings is not reviewed, potentially introducing publication bias (Kepes et al., 2012). Finally, while this review paper offers an initial discussion of the implications of the ongoing crisis triggered by the Covid-19 pandemic for marketing and AI, we believe that the real impact of this disruption is not yet fully understood. Hence, more research will be necessary to obtain a complete account of how pandemics and other unforeseen events impact marketing and AI. Despite such limitations, our study suggests several directions that we hope will inspire future studies and attract further attention to this timely topic from both scientific and societal standpoints.

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Figure 1: Methodology protocol

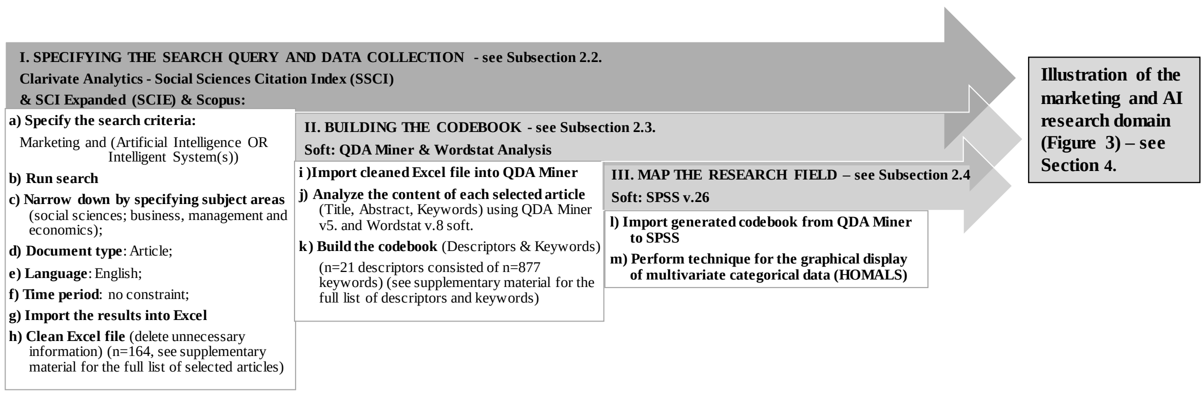

Figure 2: Publishing frequency over time

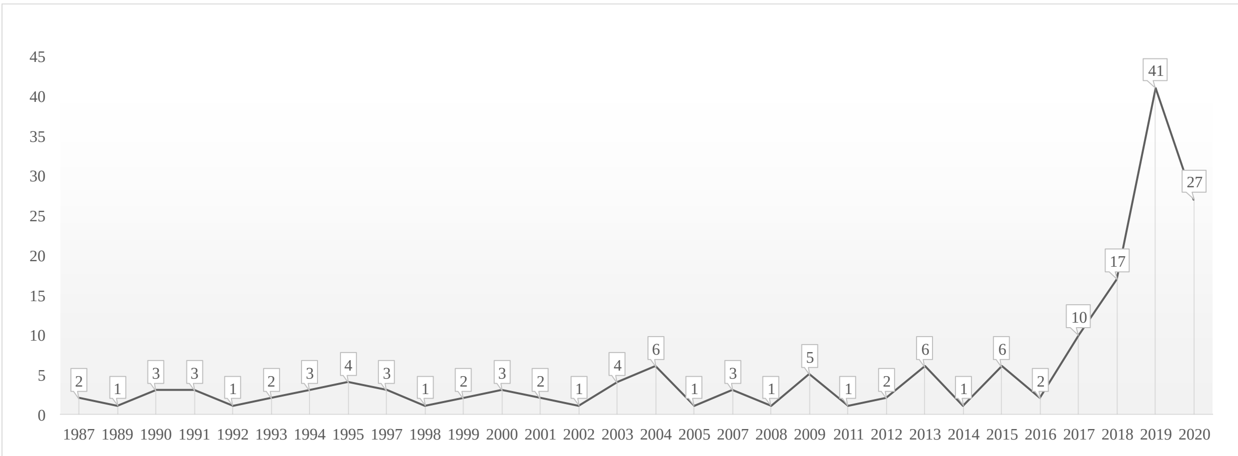

Figure 3: Map of the marketing and artificial intelligence research field.

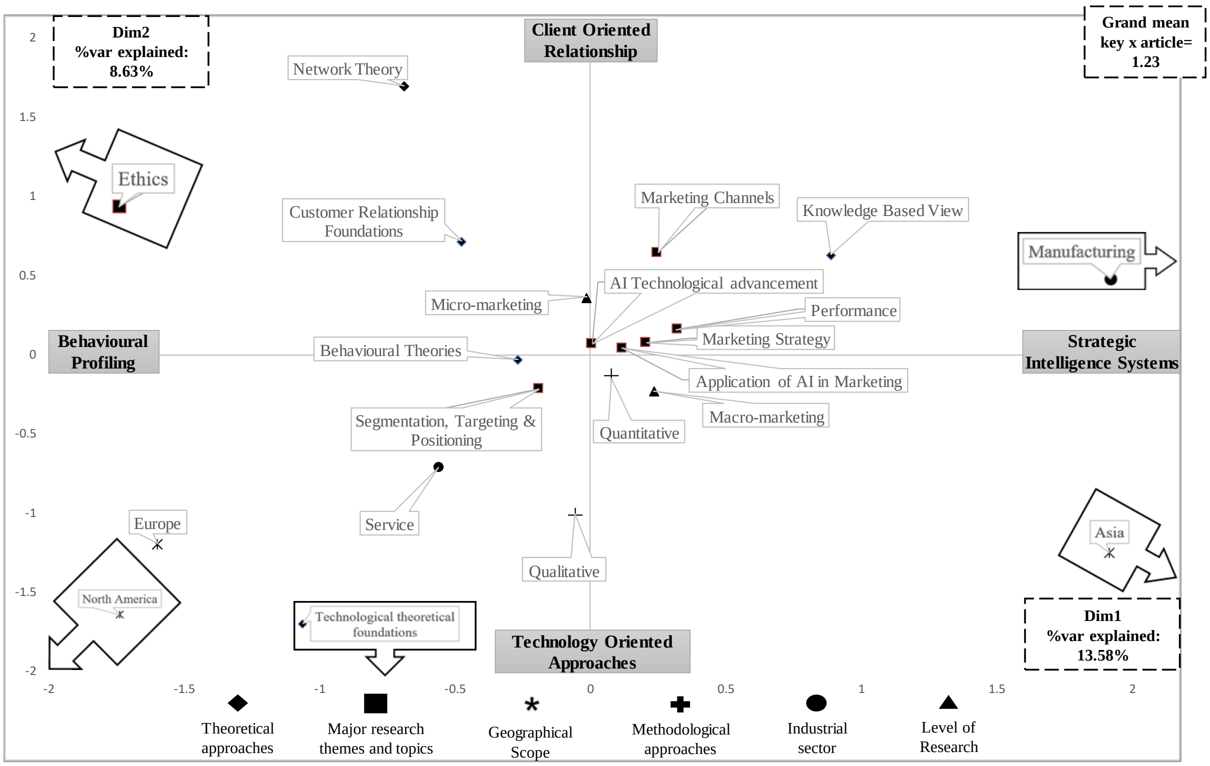

Table 1: Notable references for the development and construction of AI and Marketing framework[5]

Author	Title	**Type of review** (according to Paul & Rialp-Criado, 2020)	**Methodology** (according to Furrer et al., 2020)	Sample	Time Span	Database	Source	Overview and findings
Martínez-López & Casillas (2013)	Artificial intelligence-based systems applied in industrial marketing: a historical overview, current, and future insights	Structured review	Qualitative – Expert-based survey	50 articles	1972-2011	Scopus	Journals /conferences/ research/ book chapters	Research on the intersection of AI and industrial marketing is still scarce and unexplored. The vast majority of research is concentrated in the last decade and relates to ad-hoc intelligent systems based on a diverse range of AI approaches, such as fuzzy logic, neural networks, dynamic programming, and optimization algorithms, among others.
Syam & Sharma (2018)	Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice	Structured review	Qualitative – Expert-based survey	n.a.	n.a.	n.a.	n.a.	AI facilitates marketing effectiveness at each stage of the business-to-business sales funnel. Authors discuss the impact of machine learning and AI and propose future research avenues for sales processes regarding prospecting, pre-approach, approach, presentation, overcoming objections, close, and follow-up.

[5] Considering Bradford (1934) and Garfield's (1990) suggestions that papers published in the top journals of a field are more likely to push the boundaries of the research field, in this manuscript, we primarily use papers published in top journals. To identify the top journals, we referred to the Chartered Association of Business Schools (CABS) journal ratings of 2018 and considered those that were ranked at Level 3 or above (Dabić et al., 2020). Other articles are acknowledged throughout the manuscript but, due to word limits, are not presented in Table 1 within the reviewed manuscript.

Author	**Title**	**Type of review** (according to Paul & Rialp-Criado, 2020)	**Methodology** (according to Furrer et al., 2020)	**Sample**	**Time Span**	**Database**	**Source**	**Overview and findings**
Davenport et al. (2020)	How artificial intelligence will change the future of marketing	Structured review	Expert-based survey	n.a.	n.a.	n.a.	n.a.	Building on insights from marketing, social sciences, and computer science/robotics, the authors propose a framework to help customers and firms anticipate how AI is likely to evolve. The authors outline three AI-related dimensions: levels of intelligence, task type, and whether or not the AI is embedded in a robot, highlighting the potential effects of AI implementation through cost reduction and enhanced customer service.
Kumar et al. (2020a)	Influence of new-age technologies on marketing: A research agenda	Structured review	Expert-based survey	9	n.a.	n.a.	Journals	Focusing on the respective roles of IoT, AI, ML, and Blockchain in marketing, the authors outline the importance of the implementation of technology with regards to marketing outcomes, the necessity for financial and human resources, and the subsequent impact on customer relationships.
Kumar et al. (2020b)	Digital mediation in business-to-business marketing: A bibliometric analysis	Bibliometric review	Citation study	119	1999-2019	Scopus/ Google Scholar/Business Source Premier/ISI Web of Science-Social Science Citation Index	Journals and Conference Proceedings	Synthesizing two decades of literature on digital mediation in business-to-business marketing, the authors outline the major changes to the research field affected by the emergence of Internet research and business-to-business technology, the evolution of e-commerce, and the new focus on social media. The authors recommend further research on the intersection of social media and tools, channels, models, and metrics.

Author	Title	Type of review (according to Paul & Rialp-Criado, 2020)	Methodology (according to Furrer et al., 2020)	Sample	Time Span	Database	Source	Overview and findings
Loureiro et al. (2020)	Artificial intelligence in business: State of the art and future research agenda	Structured review	Citation study	404	1977-2020	Scopus / ISI Web of Science	Journals indexed in business-related categories	This review summarizes the role of AI within the general business field. The findings of this study reveal 18 different topics that have attracted scholarly attention regarding AI's applicability, ranging from learning to marketing and manufacturing. Accordingly, the authors reveal that marketing is among the topics in which AI has attracted the most attention from researchers and practitioners. Finally, the authors propose future trends related to AI's effects on internal stakeholders, external stakeholders, and governmental policymaking.
Mustak et al. (2020)	Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda	Bibliometric review	Citation study	214	1960-2019	ISI Web of Science	Journals indexed in marketing-related categories according to CABS list and non-marketing related according to Harzing Journal Quality List.	Building on insights from 214 articles indexed in the Web of Science Database, using CiteSpace and VOSviever, the authors outline the countries, universities, and authors that have contributed to the development of AI in Marketing, presenting the predominant research topics. Furthermore, the findings of the study highlight future research opportunities related to two interrelated relevant streams of research: (1) increased depth and (2) increased breadth of AI within the marketing domain.

Author	**Title**	**Type of review** (according to Paul & Rialp-Criado, 2020)	**Methodology** (according to Furrer et al., 2020)	**Sample**	**Time Span**	**Database**	**Source**	**Overview and findings**
Rust (2020)	The Future of Marketing	Structured review	Expert-based survey	n.a.	n.a.	n.a.	n.a.	The future of marketing is influenced by changes in three major forces: 1) technological trends, 2) socioeconomic trends, and 3) geopolitical trends. The development of AI algorithms unveils the potential of all aspects of marketing research, education, and practice.

Abbreviations: n.a. = information not available

Table 2: Overview of the most frequent journal sources by the number of articles and reference studies published in these journals

No.	Publications	Frequency of articles	Reference studies
1	Decision Support Systems	12	Chan & Ip (2011); Chica et al. (2016)
2	Applied Marketing Analytics	10	Abbas et al. (2020); Gardé (2018);
3	Industrial Marketing Management	7	Kumar et al. (2020); Martínez-López & Casillas (2013)
4	European Journal of Marketing	6	Lee et al. (2020); Pitt et al. (2020);
5	European Journal of Operational Research	5	Baesens (2004); Montgomery et al. (1997)
6	Journal of Business and Industrial Marketing	5	Paschen et al. (2019); Wilson & Bettis-Outland (2019
7	Journal of the Academy of Marketing Science	4	Davenport et al. (2020); Steinberg & Plank (1987)
8	Electronic Commerce Research and Applications	3	Tian et al. (2018); Miralles-Pechuán et al. (2018)
9	Industrial Management and Data Systems	3	Belanche et al. (2019); Choi et al., (2017)
10	Marketing Intelligence and Planning	3	Li (2000a); Li et al. (1999);
			78.0 % of articles with IF>1.0 (JCR 2020)

Table 3: Descriptors that represent the poles of the axes.

Axes	Descriptor	Origin of the axes descriptor	Notable studies
Axis X Left	Behavioral Profiling	Behavioral Theories; Segmentation, Targeting & Positioning; Ethics	Belanche et al., 2019; Belk et al., 2020; Casabayó et al., 2004; Miralles-Pechuán, 2018; Pitt et al., 2018.
Axis X Right	Strategic Intelligence Systems	Marketing Strategy; AI Technological Advancement; Knowledge-Based View	Bonnin & Rodriguez, 2019; Gardé, 2018; Paschen et al., 2020; Yazici et al., 1994.
Axis Y Upper	Client Orientated Relationship	Customer Relationship Foundations; Marketing Channels; Micro-marketing	Daskou & Mangina, 2003; Kumar et al., 2019; Moriuchi, 2019; Payne et al., 2018; Paschen et al., 2020; Steinhoff et al., 2019.
Axis Y Lower	Technology Orientated Approaches	Technological Theoretical Foundations; Macro-marketing, Services	Tam et al., 1994; Weber & Schütte, 2019; Wirtz et al., 2018; Zenobia et al., 2009.

Table 4: AI and Marketing: future research trends and research questions

Future Research Trends	**Research Questions**
Acceptance of AI technology	To what extent do users' cognitive structures (e.g., levels of attention) affect the relationship between behavioral intentions to use AI technology and actual AI use?
	How do relational elements, such as trust and rapport, affect customers' acceptance of AI technology?
	Do relational and socio-emotional elements act as substitutes or complements to factional elements in endorsing customers' acceptance of AI technology?
Adoption and use of AI technology and applications	What role do emotion-related aspects, such as fun and curiosity, play in the adoption and use of AI-based applications?
	How do the demographic characteristics of users (e.g., digital natives, digital immigrants, gender) affect their likelihood of adopting or using AI technology?
	How do cultural differences within and across nations affect users' attitudes with regards to AI?
	How is the relationship between perceived humanness and the adoption and use of AI moderated or mediated by trust?
	Can the adoption of AI improve targeting by means of a more efficient and effective communication strategy?
Revolution of the labor market and marketers' competences	To what extent does AI augment organizational performance in terms of employer attractiveness and employee satisfaction?
	Does AI affect the balance and transfer of soft and hard skills across organizational levels (horizontally and vertically)?
	How are marketers coping with digital and data analytics upskilling and reskilling?

Future Research Trends	**Research Questions**
Role of institutional support	To what extent do public policies affect the adoption of AI technology?
	What is the role of institutional initiatives, at a national and/or international level, in promoting the effective adoption of AI?
	How can AI improve relationships between institutions and clients?
Importance of data protection and ethics	Which marketing strategies enabled by AI developments are more likely to change under the General Data Protection Regulation?
	How does the General Data Protection Regulation affect the AI revolution in marketing?
	To what extent do ethical principles (e.g., transparency, justice and fairness, non-maleficence, responsibility, and privacy) affect the adoption and use of AI in marketing?
	Do differences in ethical standards affect AI in marketing in terms of creating a win-win-win situation for all involved (individuals, firms, and all other stakeholders)?
Impact of COVID-19 pandemic on AI in Marketing	To what extent are marketers willing to gather and share data - both existing and new - in order to inform new AI marketing models?
	Has the COVID-19 pandemic changed marketers' approaches to data protection? If so, how?
	In light of the COVID-19 pandemic, what role do AI-powered marketing tools play in understanding consumers' attitudes, beliefs, and behaviors?