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Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda

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ABSTRACT

The rapid advancement of artificial intelligence (AI) offers exciting opportunities for marketing practice and academic research. In this study, through the application of natural language processing, machine learning, and statistical algorithms, we examine extant literature in terms of its dominant topics, diversity, evolution over time, and dynamics to map the existing knowledge base. Ten salient research themes emerge: (1) understanding consumer sentiments, (2) industrial opportunities of AI, (3) analyzing customer satisfaction, (4) electronic word-of-mouth–based insights, (5) improving market performance, (6) using AI for brand management, (7) measuring and enhancing customer loyalty and trust, (8) AI and novel services, (9) using AI to improve customer relationships, and (10) AI and strategic marketing. The scientometric analyses reveal key concepts, keyword co-occurrences, authorship networks, top research themes, landmark publications, and the evolution of the research field over time. With the insights as a foundation, this article closes with a proposed agenda for further research.

1. Introduction

What if artificial intelligence (AI) itself were used to investigate the current literature on AI in marketing? That is what we do in this study!

Having received more than US$5 billion in venture capital investments in just the past two years, artificial intelligence (AI) is poised to exert transformative effects on markets and marketing around the world (PricewaterhouseCoopers, 2017; Rangaswamy et al., 2020; Insights, 2018). Marketing increasingly relies on its algorithms, which mimic human cognitive functions and exhibit aspects of human intelligence (Huang & Rust, 2018; Rangaswamy et al., 2020; Russell & Norvig, 2016; Sterne, 2017), such that 72% of marketers cite AI as a business advantage. Consumers benefit from these applications, in the form of decreased costs, more diverse service channels, innovative breakthroughs, and opportunities for expanded human creativity and ingenuity when tedious, repetitive tasks are performed by AI (Haenlein & Kaplan, 2019; PricewaterhouseCoopers, 2017; Smart Insights, 2018). This revolution of AI usage in marketing, and its potential for producing superior value outcomes, has sparked substantial research attention (Davenport, Guha, Grewal, & Bressgott, 2020; Haenlein & Kaplan, 2019; Huang & Rust, 2018), prompting, for example, applications of intelligent technology (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017); descriptions of services enabled, facilitated, and delivered by various technologies (Rust & Huang, 2012); investigations of AI-powered robotics (Lu et al., 2020; Wirtz et al., 2018); explorations of AI-led marketing and sales strategies (Davenport et al., 2020); considerations of how AI-enabled delivery can lead to cost-effective service excellence (Wirtz & Zeithaml, 2018; Wirtz, 2020); proposals of AI-enabled platform business models (Wirtz, So, Mody, Liu, & Chun, 2019); investigations of the impact of AI chatbot disclosures on customer purchases (Luo, Tong, Fang, & Qu, 2019); considerations of effects on workforces (Davenport & Kirby, 2015) and redefinitions of AI-enabled workplaces (Chui, Manyika, & Miremadi, 2015); and discussions of digital technologies as driving forces of work and life (McAfee & Brynjolfsson, 2016).

Despite this extensive list, marketing still lacks a cohesive understanding of how AI technologies have been applied thus far and how they should be in the future (Haenlein & Kaplan, 2019; Paschen, Kietzmann, & Kietzmann, 2019). That is, it needs literature analyses to scrutinize and synthesize the use of AI in marketing and pave a concrete

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path for future-focused academic research. Objective, reflective analyses are crucial to evaluate any extant knowledge base, identify knowledge gaps, and evaluate research effectiveness and productivity (Huang & Rust, 2018; Russell & Norvig, 2016), for both researchers and publication outlets or journals (2013;; Lowry, Romans, & Curtis, 2004). Indeed, where and how scholars publish represent essential aspects of the identity of the marketing discipline, reflecting its value systems, aspirations, paradigms, reward systems, cultural conduct, and political hierarchy (2013;; Garfield, 2006; Lowry et al., 2004). Therefore, with this study, we investigate dominant research topics related to AI in marketing, outlining key themes, influential publications, and networks among authors and journals, to provide a clear view of the extant knowledge base.

We apply two complementary analytical approaches to examine the evolution and structure of the research field. First, to identify dominant, salient topics, we undertake topic modeling and apply natural language processing, machine learning, and statistical algorithms. Second, using scientometric techniques, we generate further insights about authors and research networks, as well as establishing keyword co-occurrence rates, identifying landmark publications, and depicting the evolution of the field over time (Lowry et al., 2013; Nikolenko, Koltcov, & Koltsova, 2017; Zhao, Tang, & Zou, 2019).

In turn, this study makes four contributions. First, the combination of advanced topic modeling algorithms, established through text analytics techniques, and of scientometric analysis, enables a highly objective, robust, structured, and comprehensive review of this rapidly expanding research domain than traditional literature reviews and analyses can provide (Vanhala et al., 2020). Second, our systematic, data-driven approach reveals 10 dominant AI research topics in marketing, which we can classify as consumer research or organization and strategy–related research. Third, the scientometric analysis produces information maps of co-citation clusters, landmark articles, conceptual and theoretical foundations, and reciprocal interconnections of concepts on the basis of their paired presence in extant literature. Such a comprehensive approach establishes a broad understanding and in-depth insights, without restricting the analysis to any predesigned aspects. Fourth, we offer an extensive discussion of research gaps that in turn produces a robust agenda for increasing the depth and breadth of AI research in marketing.

After we establish the conceptual underpinning of this study in Section 2, we explicate the methodological details in Section 3. Section 4 contains descriptive details of the reviewed publications. In Section 5, we review the salient topics of research on AI in marketing, and then in Section 6, we report the scientometric analysis. Finally, we discuss the results and conclude with concrete recommendations for examining multiple overlooked facets of AI in marketing in Section 7.

2. Conceptual underpinnings

According to the American Marketing Association (AMA, 2017), "Marketing is the activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large." Furthermore, AMA (2017) defines marketing research as the function that links the consumer, customer, and public to the marketer through information. Such information is used to identify and define marketing opportunities and problems; generate, refine, and evaluate marketing actions; monitor marketing performance; and improve understanding of marketing as a process. Recent technological advances allow AI to function in virtually all of these domains (Haenlein & Kaplan, 2019; Huang & Rust, 2018; Martínez-López & Casillas, 2013).

Technological advancements frequently lead to structural shifts in business paradigms, as is true of AI in marketing (Kumar, Rajan, Venkatesan, & Lecinski, 2019). Improvements in AI enable companies to stay competitive in increasingly data-oriented marketing landscapes (Nunan & Di Domenico, 2013; Salminen, Yoganathan, Corporan, Jansen, & Jung, 2019; Smart Insights, 2018), so many companies have invested in it to facilitate various marketing-related tasks, such as chatbots, customer journey optimization, content research and creation, customer relationship management, image recognition, search engine optimization, personalization, profiling, and strategic planning (Haenlein & Kaplan, 2019; Luo et al., 2019; Netzer, Feldman, Goldenberg, & Fresko, 2012; Zhao, 2013).

In this paper, we adopt the definition of AI from Haenlein and Kaplan (2019, p. 5), as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". However, we also note that in marketing research, AI is used as an umbrella term. It covers multiple activities and concepts, with the broad notion that various types of computers, through the use of software and algorithms, can facilitate or perform tasks that previously required human cognitive abilities (De Bruyn, Viswanathan, Beh, Brock, & von Wangenheim, 2020; Haenlein & Kaplan, 2019; Huang & Rust, 2018; Kumar et al., 2019). Accordingly, extant marketing studies use terms like machine learning, service robots, automation, big data, neural network, natural language processing, and the Internet of things (IoT) to refer to AI (Huang & Rust, 2018; Kumar et al., 2019; Marinova et al., 2017; Netzer et al., 2012; Nunan & Di Domenico, 2013; Salminen et al., 2019; Tirunillai & Tellis, 2014; Wirtz et al., 2018). Considering its vast prospects, it is not surprising that AI has attracted such significant research attention.

3. Methodology

To establish a foundation of AI in marketing, the major topics studied, and connections among researchers and major studies, we applied two complementary sets of analytical algorithms: topic modeling and scientometric analysis (Booth, Sutton, & Papaioannou, 2016; Nikolenko et al., 2017; Zhao et al., 2019). For the topic modeling, we used Latent Dirichlet Allocation (LDA), which reveals co-occurrences among words, as well as long-span latent topic information. It allowed us to investigate topics that receive the most research attention, identify underlying topical trends, and find the most relevant documents for each topic (Jacobi, van Atteveldt, & Welbers, 2016; Nikolenko et al., 2017). The scientometric analyses refer to co-author, co-word, and co-citation clusters, so they objectively depict the status quo (Zhao et al., 2019). That is, such analyses establish a comprehensive view and evaluation of studies of AI in marketing according to a quantitative assessment of scientific activities (Garfield, 2006; Lowry et al., 2004; Zhao et al., 2019). In the following subsections, we provide details of the data collection, followed by information on the analytical algorithms and procedures.

3.1. Data collection

We used documents indexed in the Web of Science (WoS) database (Vanhala et al., 2020). This database offers wide coverage of scientific publications from 3,300 carefully selected publishers and more than 12,000 high impact journals, as well as a reference index with more than 1 billion cited references, starting from 1900. The index reflects Garfield's law of document sets and Bradford's discrete law, subject to strict procedures and high standards (Borgman & Furner, 2002; Zhao et al., 2019). In addition, WoS supports data curation for each cited reference in any bibliographic record, which makes it valuable for both topic modeling and scientometric analysis (Clarivate Analytics, 2017; Reuters, 2017).

We systematically identified keywords for use in our study by performing an initial search using the keyword combination "artificial intelligence AND marketing" and downloading the top 20 most cited papers. We carefully examined these papers and listed several terms and word combinations they used to denote the same or closely related concepts. We included all these terms as keywords in our search for related data. The complete search criteria and keywords used are presented in Table 1.

The resulting search yielded 1,039 bibliographic records, including articles, conference papers, and periodicals. To enhance the focus of our review, we systematically cleaned the data set by requiring articles to be published in peer-reviewed international journals (607 out of 1,039). Such journals represent a field's most recent validated knowledge and offer the highest impact (Booth et al., 2016). Next, we retained only those articles published in marketing journals, which we identified by applying two commonly accepted categorizations, the Journal Quality List by Harzing (5 February 2020 version) and the Academic Journal Guide by the Chartered Association of Business Schools (CABS, 2018). This restriction left 87 entries, whose titles, abstracts, and, if needed, introductions and conclusions we reviewed carefully. Furthermore, 127 articles published in journals not categorized as marketing journals by Harzing (2020) or CABS (2018) (e.g., *California Management Review, Harvard Business Review, International Journal of Knowledge Management, MIS Quarterly, Research Policy*) still appeared to offer valuable insights into AI in marketing, so we also included them in our analysis. Finally, we downloaded metadata for these 214 articles, which include print features, authors' names, corresponding authors' countries, total number of publications, citation counts with total citations, average article citations, number of citing articles with and without self-citations, journal sources, keywords, countries and regions, and author-level metrics (e.g., h-, m-, g-indices) (Martynov, Klima-Frysch, & Schoenberger, 2020).

3.2. Data analysis

We applied a structured workflow based on the LDA algorithm for the topic modeling step (Pravakaran, 2018), in line with the principles recommended by Nikolenko et al. (2017). The assemblage of D articles is assumed to contain T topics expressed through W different words. Each article $d \in D$ of length N_d is modeled as a discrete distribution (d) over the set of topics $(zj = t) = (d)t$, where z is a discrete variable that defines the topic for each word instance $j \in d$. Each topic in turn corresponds with a multinomial distribution over the words, $p(w|z_j = t) = \phi_w^{(t)}$. The Dirichlet priors α can be assigned to the distribution of topic vectors θ, θ ~ Dir(α), similar to β for the distributions of words in topics, ϕ ~ Dir(β). We used Python programming language (Version 3) for algorithm development, along with the Jupyter Notebook (Update 2020) platform to generate the visual illustration.

With gensim library's native LdaModel, we generated meaningful topics, then created visualizations using the matplotlib library. We tokenized and cleaned the texts, such as by removing stopwords and structural words from the abstracts (e.g., purpose, aim, approach, method, contribution) (Blei, 2012). Next, we built word bigrams, such as linking the words *big* and *data* as *big_data*. We also used algorithms to lemmatize each word in its root form (e.g., *approaching* rooted to *approach*) (Wallach, 2006). Finally, we applied the LdaModel library to develop the corpus and the dictionary. This model uses machine learning and natural language processing to identify semantic topics and their clusters with clear dominance in the overall domain (Andrzejewski, Zhu, & Craven, 2009; Jacobi et al., 2016; Pravakaran, 2018).

In the scientometric analyses, we mapped knowledge in the scientific area (Lowry et al., 2004; Zhao et al., 2019), according to two complementary platforms: VOSviewer (Version 2020) and CiteSpace (Version 2019). We extracted and imported full bibliometric records and cited references from WoS in a tab-delimited format. For the network layout and network clustering, we relied on co-occurrence networks based on textual data, in which relevant and non-relevant terms were distinguished using algorithms (Zhao et al., 2019). These efforts supported our analysis of key concepts, co-citations, and author networks. We list all the scientometric analyses we performed in Table 2.

For the co-citation cluster analysis, we identified semantic correlations based on citation relationships – the frequency with which other studies cite two papers together. The more co-citations two documents earn, the higher their co-citation strength, and the more likely it is that they are semantically related. We thus could identify landmark publications that represent founding pillars of the research domain, even if they are not included in our literature pool. That is, they provide core concepts, ideas, principles, and doctrines that have allowed research on AI in marketing to develop and grow (Martynov et al., 2020).

A density visualization offers a representation of the distribution of variables, using a kernel density estimate to predict the probability density function of variables. For this study, we apply it to the prominence of each keyword and its related concepts. Then we integrate our keyword co-occurrence analysis to map the conceptual structure of the domain, according to a dimensionality reduction technique. We thus can identify clusters of concepts that focus on mutual research phenomena. With a temporal perspective, we delineate how the central keywords and concepts have evolved over time. Finally, the authorship cooperation and journal co-citation analyses reveal collaborations among leading researchers in the field of AI in marketing research, and specify which journals form the core of its knowledge base (Lowry et al., 2004; Martynov et al., 2020).

4. Descriptive details of extant publications

The first marketing article on AI was published in 1960 (Head, 1960), followed by a second in 1962 (Goeldner, 1962), both in *Journal of Marketing*. Both were ahead of their time, and we find a long gap after their appearance (Fig. 1), such that the third article only was published

Table 1
Database search details of the study.

	Search Terms
Field Tag: Title (TI)	TI=("AI" OR "artificial intelligence" OR "machine learning" OR "robot OR "automation" OR "big data" OR "neural network*" OR "text mining" OR "natural language processing" OR "data mining" OR "soft computing" OR "fuzzy logic" OR "biometrics" OR "geotagging" OR "wearable*" OR "IoT" OR "internet of things")
Boolean:	AND
Field Tag: Topic (TS)	TS=(Marketing)
Boolean:	AND
Field Tag: Research Area (SU)	SU=(Business and Economics)

Note: Asterisks (*) are used to capture plural forms.

Table 2
List of scientometric analyses performed in this study.

Analytical Method	Algorithmic computational Tool	Purpose
Co-citation clusters	CiteSpace	To gain an overview of the semantic similarities and connections between the studies on AI in marketing
Landmark publications	CiteSpace	To specify and determine the 'centrally-located' documents based on co-citation patterns
Density visualization	VOSviewer	To identify the conceptual/ theoretical base
Keyword co-occurrence analysis	VOSviewer	To identify the mutual interconnectedness of concepts based on their paired presence within the literature base
Mapping central keywords over time	VOSviewer	To Examine the evolution of research focus in the research base
Authorship cooperation and journal co-citation analysis	VOSviewer	To investigate the scientific collaborations between the leading researchers in the field, and the core strength of the intellectual domain and strengthening cooperation in science

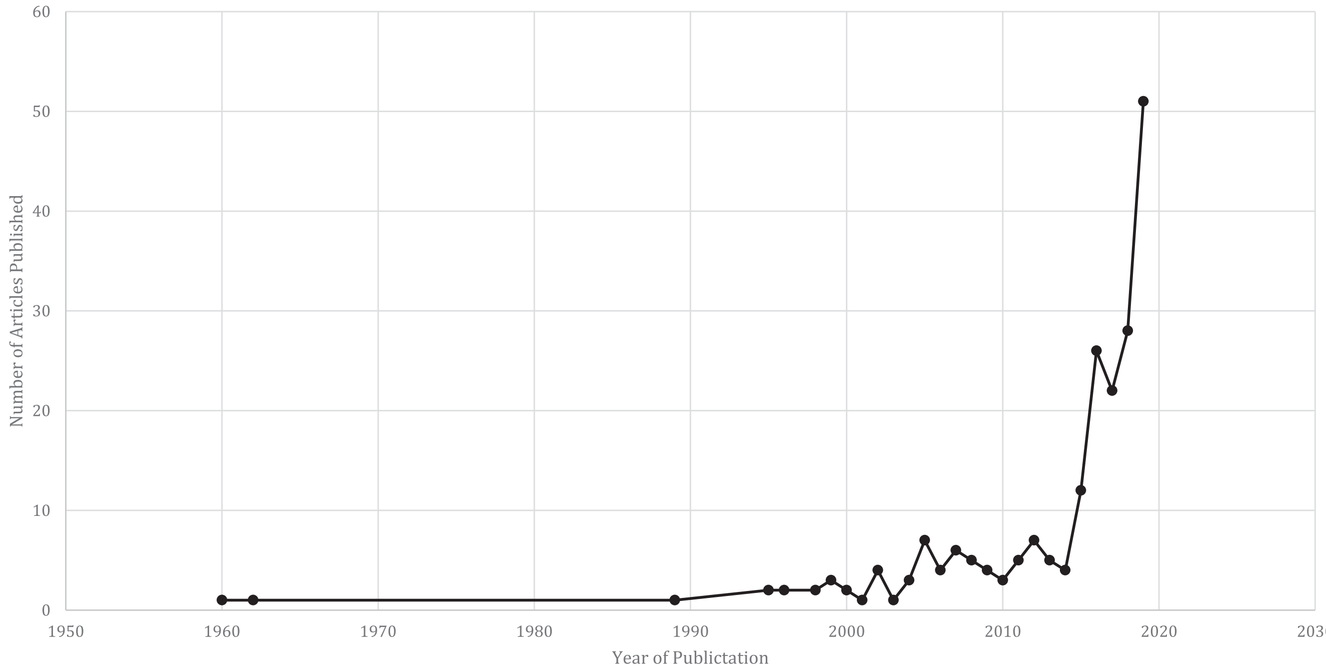


Fig. 1. Number of publications per year on AI in marketing.

in 1989. The number of articles stayed low and did not reach double digits until 2015. But after 2016, we observe a rapid increase in publications, such that at least 20 articles appear each year, and 51 articles were published in 2019. Demonstrating the growing interest of researchers in the field, this upsurge parallels technological advancements in AI and its increased use in marketing.

The trend also spans a wide range of journals, both in general management and marketing and more specialized outlets. As Table 3 shows, the greatest number of relevant articles published by general management journals appears in *Journal of Business Research* (15), starting in 1996 (Bejou, Wray, & Ingram, 1996), followed by *Industrial Marketing Management* (10), *International Journal of Market Research* (8), and *Technological Forecasting and Social Change* (8). The prominent presence of specialized business-to-business (B2B) journals, such as *Industrial Marketing Management* and *Journal of Business and Industrial Marketing*, among the top five publication outlets emphasizes the importance of AI for domain-specific B2B scholars. Furthermore, publications in *Tourism Management* and *International Journal of Retail & Distribution Management* suggest context-specific considerations of AI in marketing.

With regard to countries ranked by research output, we find that research on AI in marketing comes from three concentrated geographic areas: United States, Central and Southern Europe, and East Asia, as we illustrate in Fig. 2. Moving to the university level, we note similar trends, such that universities from these three groups of countries dominate too (Fig. 3). Georgia State University tops the list (5 articles), followed by Aalto University, Korea University, and University of Granada (4 articles each), then London Business School, Massachusetts Institute of

Table 3
Top publication outlets and their respective number of articles on artificial intelligence in marketing (Till the year 2019, as 2020 is not completed yet).

	Year of Publication																						
Name of the Journal	95	96	99	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	Total
Journal of Business Research		1	1		1		2			1						1			3	1		4	**15**
Industrial Marketing Management	1			1				1	1		2		1			1	1		1				**10**
International Journal of Market Research							1	1				1	1			1					1	2	**8**
Technological Forecasting and Social Change																			3		2	3	**8**
Journal of Business & Industrial Marketing											1										4	2	**7**
Tourism Management			1			1			1									1	1		2		**7**
Technology Innovation Management Review																					2	4	**6**
Business Horizons																		2	1	1			**4**
International Journal of Retail & Distribution Management								1		1												2	**4**
Journal of Product Innovation Management	1													1						2			**4**
Marketing and Management of Innovations																				3		1	**4**
Marketing Science														1	1				1	1			**4**

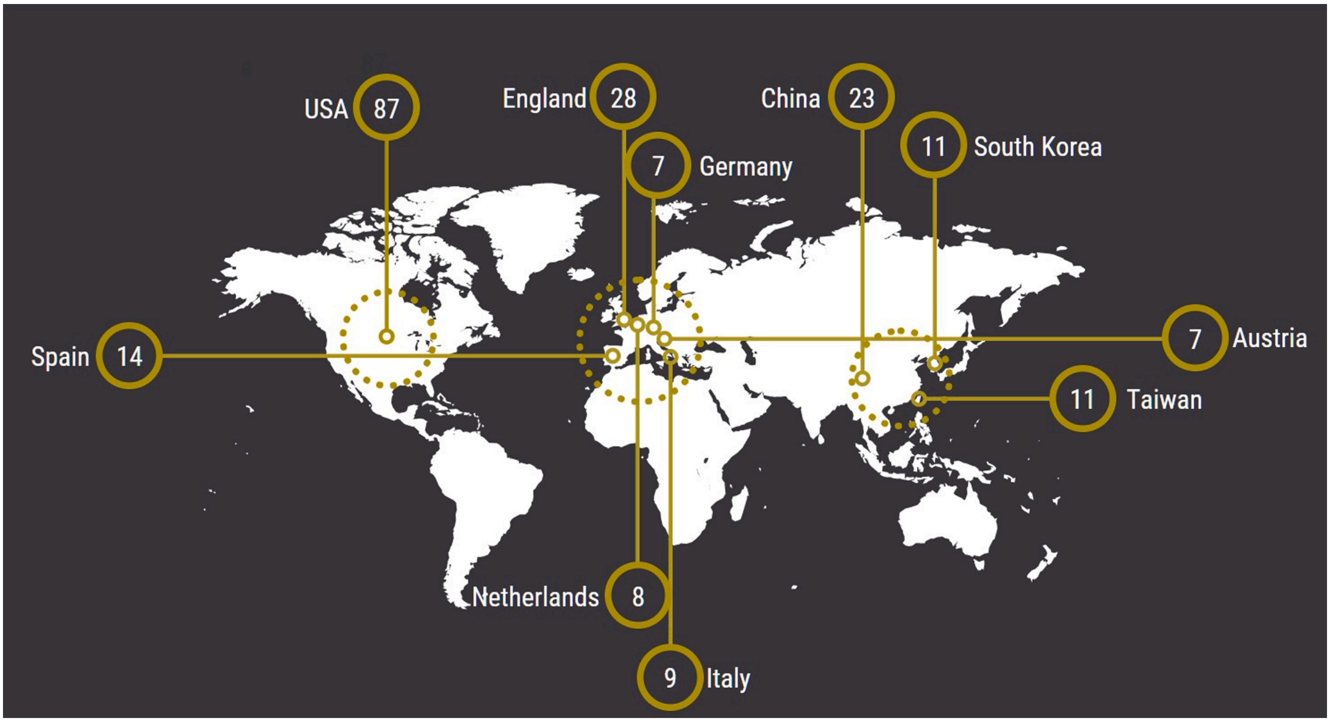


Fig. 2. Top 10 countries in terms of research output on AI in marketing.

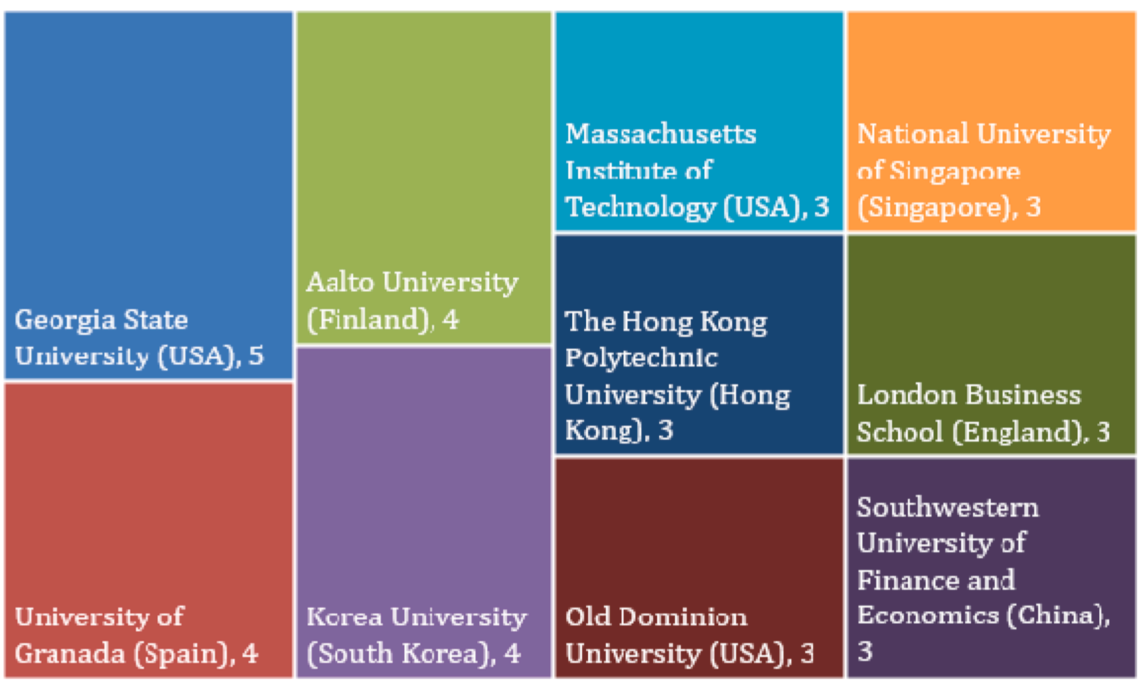


Fig. 3. Top 10 universities in terms of research output on AI in marketing.

Technology, National University of Singapore, Old Dominion University, Southwestern University of Finance and Economics, and Hong Kong Polytechnic University (3 articles each). These relatively low numbers of publications per academic institution indicate a lack of any strong concentration of academic research. Instead, research into AI in marketing is spread among many institutions and geographic regions. Still, the dominance of the United States is striking, in that it accounts for as much research as the next five countries combined (40.7% of articles).

5. Topic modeling

Because the vast amount of information available goes beyond the processing capacities of humans (Andrzejewski et al., 2009; Wallach, 2006; Wang & Blei, 2011), topic models are valuable. We apply them to uncover hidden semantic structures and topics in the large body of unstructured, natural text we gathered, using language processing, machine learning, and statistical algorithms (Blei, 2012; Wang & Blei, 2011). That is, we model the latent and semantic topics of all 214 scientific articles on AI in marketing. In the word cloud in Fig. 4, a term that appears more commonly in the texts appears larger. Thus, a cursory look at the word cloud provides a quick snapshot of the focus of written material on AI in marketing.

Our topic modeling analysis reveals that extant studies focus on several key domains (Table 4). For parsimony, we categorize these topics into two groups: consumer research and organizational or strategic marketing issues. We also consider the connectedness, correspondence, and relative significance of these topics in this section.

5.1. Consumer-related research

Six topics belong to the category that pertains to consumer-related research. Using the topic numbers auto-assigned by the applied algorithms (and detailed subsequently in Fig. 6), we identify them as follows: understanding consumer sentiments (Topic 1), analyzing customer satisfaction (Topic 3), gaining insights from electronic word of mouth (eWOM) (Topic 4), using AI for brand management (Topic 6), measuring and enhancing customers' loyalty and trust (Topic 7), and using AI for customer relationship management (Topic 9).

Studies related to Topic 1 concentrate on both understanding and predicting customer sentiment, such as by leveraging big data to conduct in-depth investigations of online feedback, attitudes, or perceptions (Chong, Li, Ngai, Ch'ng, & Lee, 2016). Data that offer customer insights tend to be unstructured, such as text, images, audio, and video. The sheer volume of these data means that standard analytical procedures are computationally untenable (Liu, Singh, & Srinivasan, 2016). By using AI, marketers can identify structures, underlying meanings, and dominant sentiments in the data. They also can specify consumers' demands and suggest opportunities for product and service innovation, through derived insights into unmet customer needs (Zhang, Rao, & Feng, 2018).

The research included in Topic 3 focuses on applying AI to analyze customers' attitudes, sensitivities, and behaviors (Baumann, Elliott, & Burton, 2012). For example, researchers have measured the effects of various marketing initiatives using neural network–based AI (Ansari & Riasi, 2016). Leminen, Rajahonka, Westerlund, and Wendelin (2018) analyze about 130,000 customers' evaluations of airline services and how detailed customer satisfaction information might predict their intentions to reuse these services.

Topic 4 studies deploy AI to clarify the effects of marketing actions and activities by analyzing eWOM. For example, Tang and Guo (2015) provide initial evidence of the validity and utility of text mining, by showing that linguistic indicators generated through text analysis can predict eWOM communicators' attitudes toward a product or service. Analyzing massive amounts of online comments with machine learning techniques also provides better, quicker insights into customers' comments and reactions, such that firms can react more promptly to consumers' eWOM (Pantano, Giglio, & Dennis, 2019).

Studies categorized into Topic 6 investigate usage of AI for brand management. User-generated online content offers an enticing source for marketers to mine meanings at a high temporal frequency, so dynamic analyses through AI are promising for helping them track various dimensions' significance over time and creating dynamic maps of competitive brand positions (Tirunillai & Tellis, 2014). For example, AI tools reveal that emotional authenticity, brand partnerships, brand relationships, brand salience, and brand personality have crucial roles in priming customers' brand loyalty (Haryanto, Silva, & Moutinho, 2015).

Pertaining to the measurement and enhancement of customer loyalty and trust in Topic 7, studies show that AI can build decision support models that combine fuzzy logic with expert judgments to estimate guest loyalty, thus giving international tourist hotels tools for enhanced loyalty management efforts (Lau, Nakandala, Zhao, & Lai, 2015). Similarly, AI can assist in building recommendation-driven digital marketing strategies by offering companies various predictive models. These models incorporate big data and machine learning techniques to personalize customer rewards and encourage enhanced loyalty toward firms (Ballestar, Grau-Carles, & Sainz, 2019).

Finally, Topic 9 within the consumer-related marketing research category pertains to how AI can be deployed to maintain and enhance customer relationships. Works related to this topic show that blending IoT solutions with relationship marketing strategies benefits business performance, as well as the development of long, successful relationships (Lo & Campos, 2018). Moreover, artificial neural network analyses provide insights into the potential determinants of relationship quality (Bejou et al., 1996). With various sources of big data, researchers can create a value-justified data infrastructure that enables the focused, agile deployment of advanced customer analytics and thus the maintenance of better customer relationships (Kitchens, Dobolyi, Li, & Abbasi, 2018).

5.2. Organization and strategy–related research

The second category comprises four topics, related to marketing research devoted to firms' organization and strategy, which again are numbered automatically by the algorithm and summarized subsequently in Fig. 6.

Topic 2 comprises industrial opportunities of AI in B2B contexts, mainly to automate selling processes through innovation (Cascio, Mariadoss, & Mouri, 2010; Fish, Barnes, & Aiken Assistant, 1995; Wang & Hong, 2006). It includes AI applied to enhance market segmentation capabilities (Fish et al., 1995) and data mining employed to develop customer profitability management systems that encourage customers to

Fig. 4. Word-cloud of the prominent words in the examined literature.

Table 4
Dominant topics in research on artificial intelligence in marketing.

Topic Number	Label of the Topic	Words	Exemplary Studies
Category 1 – Consumer/customer-related research on using AI in marketing			
1	Understanding consumer sentiments	Big data, Consumer, Content, Digital, Innovation, Market, Marketing, Negative, Online, Sentiment	Chong et al., 2016; Liu et al., 2016; Zhang et al., 2018
3	Analyzing customer satisfaction	Customer, Customer satisfaction, Effect, Forecast, Growth, Marketing, Neural network, Product, Service	Ansari & Riasi, 2016; Baumann et al., 2012; Leminen et al., 2018
4	Electronic Word of Mouth (eWOM)-based insights	Analytics, Big data, Consumer, Customer, eWOM, Market, Marketing, Process	Pantano et al., 2019; Tang & Guo, 2015
6	Using AI for brand management	Brand, Consumer, Customer, Data mining, Firm, Management, Market, Segment, Strategy	Haryanto et al., 2015; Tirunillai & Tellis, 2014
7	Measuring and enhancing customers' loyalty and trust	Adaption, Big data, Consumer, Customer, Firm, Loyalty, Product, Travel, Trust	Ballestar et al., 2019; Lau et al., 2015
9	Using AI to improve customer relationships	Development, Improve, Information, Market, Marketing, Network, Performance, Relationship, Response	Bejou et al., 1996; Kitchens et al., 2018; Lo & Campos, 2018
Category 2 – Organization and strategy-related research on using AI in marketing			
2	Industrial opportunities of AI	Big data, Automation, Capability, Firm, IoT, Sales, Marketing, Opportunity, Process, Supply chain	Cascio et al., 2010; Fish et al., 1995; Wang & Hong, 2006
5	Improving market performance	Consumer, Improve, Management, Market, Marketing, Neural network, Performance, Salesperson, Service, Support	Agrawal & Schorling, 1996; Cui, Wong, & Lui, 2006; Erevelles et al., 2016; Hamid & Iqbal, 2004; Kim et al., 2005
8	Artificial intelligence and novel services	AI, Customer, Innovation, Management, Marketing, Service, System, Technology	van Pinxteren et al., 2019; Wirtz et al., 2018; Yu, 2020.
10	AI and strategic marketing	Business model, Company, Customer, Industry, Innovation, IoT, Market, Service, Strategy, Technology	Li et al., 2012; Lin & Kunnathur, 2019; Netzer et al., 2012

Notes: (i) Topic numbers are auto-generated by the algorithms used, (ii) Labels are assigned by the researchers according to the underlying commonalities.

turn towards new, more valuable goods and services instead of buying cheaper ones (Wang & Hong, 2006).

A related but distinct focus on improving market performance defines Topic 5, such that these studies aim for a better understanding of the impact of AI on various marketing activities so that firms can exploit it better (Erevelles, Fukawa, & Swayne, 2016). For example, they apply neural networks to predict market volatility (Hamid & Iqbal, 2004) or grocery brand shares (Agrawal & Schorling, 1996). Combined with genetic algorithms, artificial neural networks also can increase the accuracy of customer targeting over more traditional principal component analysis of demographic information (Kim, Street, Russell, & Menczer, 2005).

The studies in Topic 8 explore how AI can be used to create and deliver novel services. It is worth noting that several studies in this category pertain to service robots. For example, Yu (2020) investigates YouTube comments to learn general public impressions of robots as frontline hotel workers. Considering different types of robots, van Pinxteren, Wetzels, Rüger, Pluymaekers, and Wetzels (2019) examine whether human-like appearances or social functioning features are more effective for fostering customer trust. Wirtz et al. (2018) propose a conceptual approach, rooted in service, robotics, and AI literature.

The final topic, pertaining to AI and strategic marketing, Topic 10 involves strategic determinants of firm performance by converting user-generated content into insights into market structures and the competitive landscape (Lin & Kunnathur, 2019; Netzer et al., 2012). From a strategic perspective, managers' strategic intent and the industrial driving force of the IoT, combined with customer, entrepreneurial, technology, and developmental culture orientations, contribute to the development of strategic AI (Li, Hou, Liu, & Liu, 2012; Lin & Kunnathur, 2019).

5.3. Connectedness, correspondence, and relative significance of the topics

Due to its high dimensionality (i.e., number of coordinates needed to locate objects in multidimensional space) and large samples, natural language is difficult to analyze objectively (Belkina et al., 2018; Chan, Rao, Huang, & Canny, 2019). In our case, we analyzed the titles, abstracts, and associated keywords, written in natural language, from all 214 articles, leading to a large number of dimensions. Hence, to validate our topic modeling further, we used t-distributed stochastic neighbor embedding (t-SNE), which is a machine learning algorithm for the visualization of outcomes (Cao & Wang, 2017; Schubert, Spitz, Weiler, Geiß, & Gertz, 2017). By calculating the eigenvectors from the covariance matrix, t-SNE provides a representation of data in a lower-dimensional space with a maximal representation of variance.

In Fig. 5, because the algorithm is nonlinear and adapts to the underlying data, a large set of points in the high-dimensional space gets represented in lower-dimensional space, typically the 2D plane (Chen, Ibekwe-SanJuan, & Hou, 2010; Schubert et al., 2017). However, due to the reduction of the many dimensions, the axes in this low-dimensional space do not offer particular meaning (Chan et al., 2019). Rather, neighboring points in the input space should tend to be neighbors in the low-dimensional space, so we use the relative distances (or their absence) between low-dimensional points for the validation (Belkina et al., 2018; Chan et al., 2019). In our study, the multidimensional data points resonate with our 10 identified topics, such that they validate the modeled topics. Furthermore, we developed an inter-topic distance map by applying Python latent Dirichlet allocation visualization (pyLDAvis), which we present in Fig. 6. The distances between the centers of the circles demonstrate the connectedness and correspondence among topics, and the size of each circle reflects the significance of each topic within the overall literature base. The bar chart identifies the 30 most salient terms in the data set.

The inter-topic distance map in Fig. 6 also establishes the varying degrees of consideration of the prominent research topics. Topic 1, understanding consumer sentiments, is among the most significant in this research domain, closely connected with Topic 3 (analyzing customer satisfaction) and Topic 9 (using AI to improve customer relationships). It also links relatively more closely with Topic 2 (industrial opportunities of AI) and Topic 5 (improving market performance). Another proximal grouping includes Topics 7 (measuring and enhancing customers' loyalty and trust) and 8 (AI and novel services). Although Topics 6 (using AI for brand management) and 8 (AI and novel services) are somewhat close, they appear relatively farther from any of the other topics. Finally, Topic 10 (AI and strategic marketing) takes a standalone position.

6. Scientometric analysis

With advanced statistical algorithms, a scientometric analysis

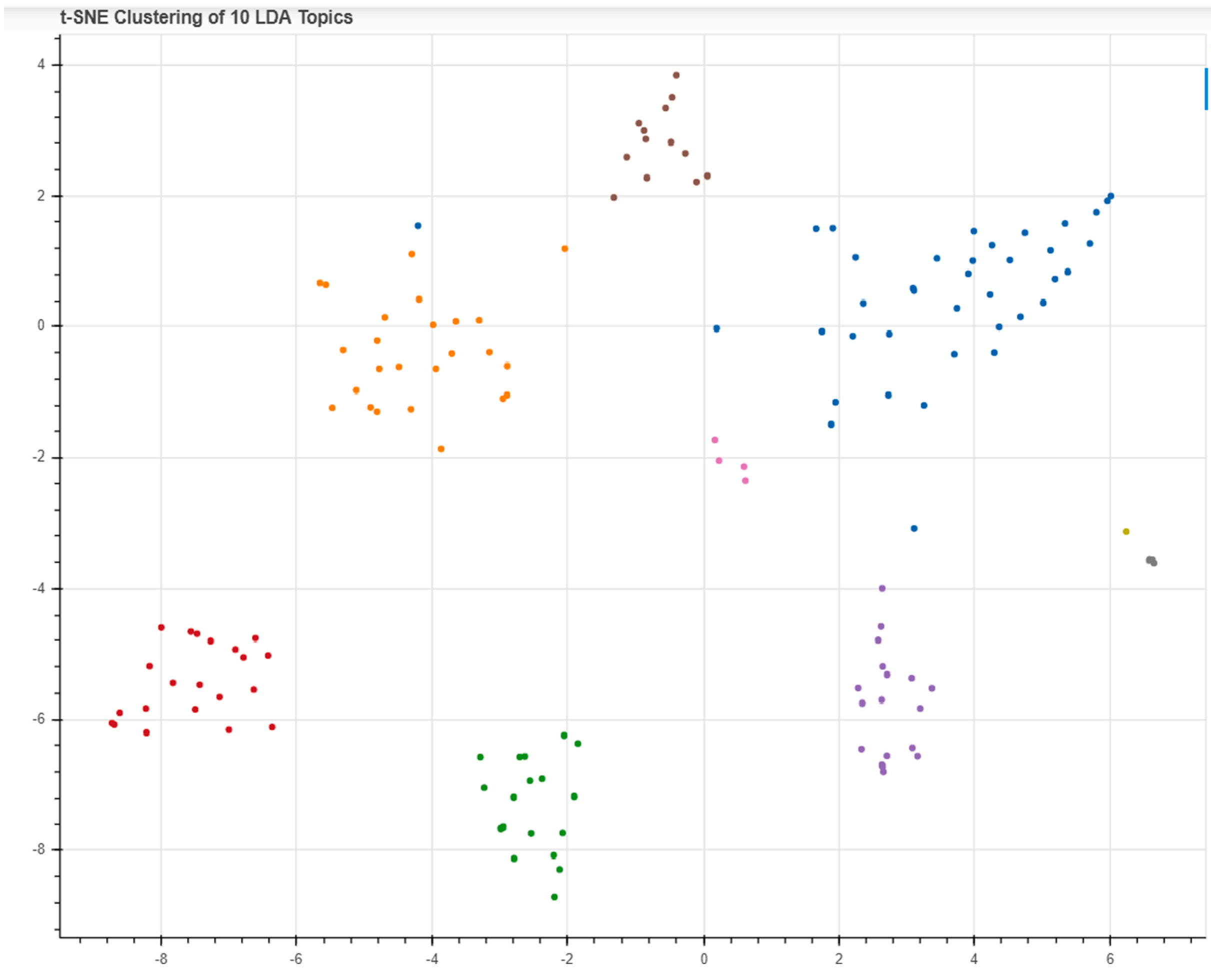


Fig. 5. T-distributed Stochastic Neighbor Embedding (t-SNE) of the modeled topics.

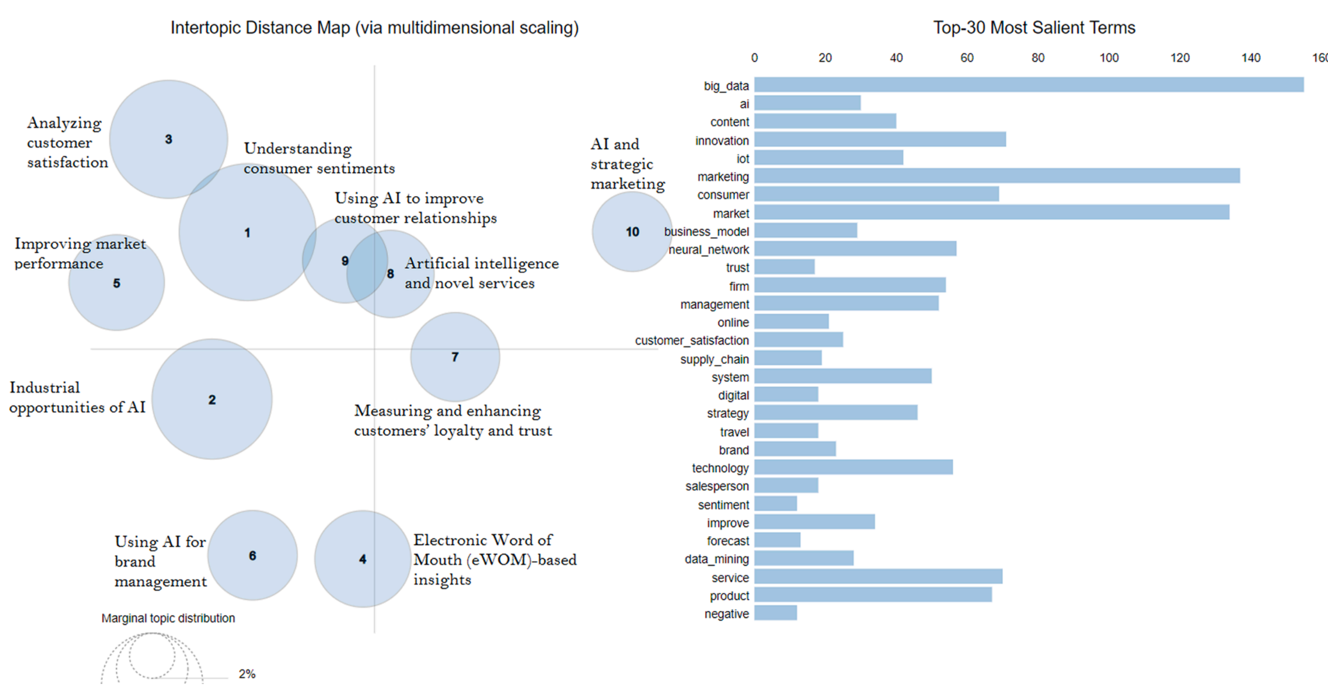


Fig. 6. Inter-topic distance map of the modeled topics.

generates a snapshot of the merits of different studies and researchers in a field (Hoeffel, 1998; Holdren, 2017). By applying it, we reduce the risk of any perceptional biases and generate insights based on more objective investigations.

6.1. Co-citation clusters

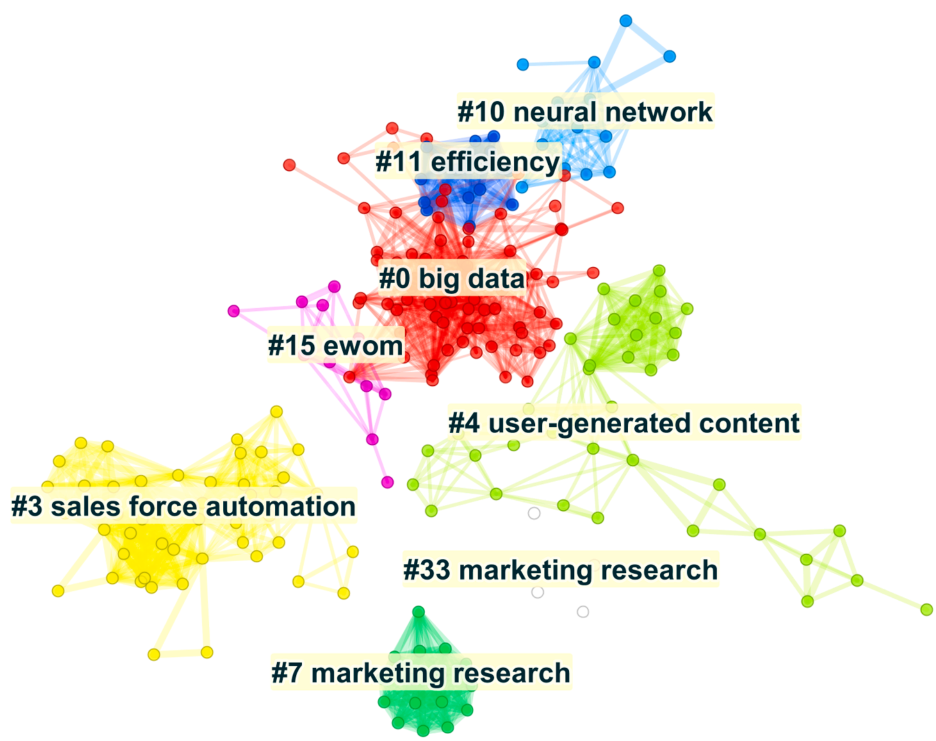
A co-citation analysis can provide a meaningful overview of the semantic similarities and connections among documents in a literature base. It facilitates sense-making, in that it integrates network visualization, spectral clustering, automatic cluster labeling, and text summarization (Chen et al., 2010; Shiau, Dwivedi, & Yang, 2017). After developing a matrix of co-citations, we can cluster the documents according to the similarity of their co-citation schematics. These resulting clusters are interpreted to indicate dominant themes (Shiau et al., 2017).

For our knowledge clustering effort, we adopt a spectral clustering algorithm and extract labels from pertinent literature in each citation cluster. Thus, in the clustering analysis chart in Fig. 7, each polygonal box represents a cluster with a homogeneous theme. The silhouette value of each cluster, calculated by algorithms, indicates network homogeneity. When the value of S approaches 1, it indicates greater homogeneity (correlation and aggregation within the cluster) and the degree of nodes (number of articles) in that cluster (Wu, Wu, & Zhang, 2019). Thus, we determine that the 10 focal themes can be assigned to eight co-citation clusters. Studies on big data take a central position; in addition to citing one another, they frequently get cited by studies on eWOM, efficiency improvements through AI, and neural networks. In contrast, studies that use AI for marketing research tend to cite only among themselves, producing their relatively isolated position in this chart.

6.2. Landmark publications

Next, we identify the landmark publications that have contributed to form and grow research on AI in marketing. For this analysis, we consider *betweenness centrality*. It is a measure of centrality in a network based on the shortest paths, such that any node with higher betweenness centrality exerts more influence over the network because more information passes through it, hence it exerts a high influence. All the nodes in a network can be assigned relative scores, with the predictions that connections to other, high scoring nodes contribute more to the focal node's score than do equal connections to low scoring nodes. Thus, a higher score means that a node is connected to multiple other nodes that have high scores themselves.

For our study, rather than simply counting the number of citations of the articles in the reviewed literature, we seek to identify the centrally located documents on the basis of co-citation patterns, because they are the articles that bind the research field. For example, Barney (1991)



Cluster ID	Auto Generated Cluster Label	Silhouette Value
0	Big data	0.719
3	Sales force automation	0.985
4	User-generated Content	0.927
7	Marketing research	0.991
10	Neural networks	0.906
11	Efficiency	0.982
15	e-WoM (Electronic Word-of-Mouth)	0.856
33	Marketing research	0.998

Fig. 7. Co-citation clusters of literature on AI in marketing.

article—Special theory forum the resource-based model of the firm: origins, implications, and prospects—is not part of our literature pool, but exerts high influence on in the extant studies on AI in marketing. For this analysis, we apply algorithms that measure how often two articles are cited together by a third, as well as how often a pair of articles cite the same third article. In both cases, the premise is that paired articles should share knowledge commonalities. In Table 5, we list the top 10 articles in terms of their centrality scores.

6.3. Density visualization

For this scientometric analysis, we conduct a keyword density analysis, which identifies words and concepts that are most prominent in the specific field. In Fig. 8, larger bubbles imply the more frequently used keywords and associated concepts; for this density visualization, we set a minimum threshold of at least five occurrences in the literature pool. It also reveals the location trends of dense point data, with color gradients, such that we can identify where groups of keywords and their associated concepts correlate.

Starting from the top left corner, we find that studies with an organizational perspective represent a dense area. They examine big data and their impacts on organizational practices, performance, competitive advantage, and so on. Moving clockwise, we find a density cluster pertaining to superior value creation for consumers through AI, involving various forms of information, risks, and innovation. Then we note multiple dense keyword clusters formed by studies that focus on, for example, IoT, web, and data mining. At the bottom, analytical studies address multiple variables, along with Bayesian networks, loyalty, nature, and RFM (Recency, Frequency, Monetary value). Finally, a cluster includes studies of computing systems that resemble biological neural networks and how AI can be used to enhance the abilities of marketers.

6.4. Keyword co-occurrence analysis

Keywords co-occurrence networks are the mutual interconnectedness of terms according to their paired presence within the literature base. In knowledge mapping

each node represents a keyword and each link represents the co-occurrence of a pair of words. The weight of a link connecting each pair represents the number of times these words co-occur in multiple articles. Therefore the co-occurrence network effectively represents the cumulative knowledge of a domain in terms of its crucial knowledge components and insights as established by patterns and strength of links between keywords that appear in the literature (Radhakrishnan, Erbis, Isaacs, & Kamarthi, 2017; Wu et al., 2019).

In Fig. 9, depicting the keyword co-occurrence network for AI in marketing, the lower-left corner pertains to studies on neural networks and their tight connections with studies of market segmentation, model development, and behavioral research. Similarly, we find strong co-occurrences across studies that focus on sales, WOM, user-generated content, and quality. In the center, the highest co-occurrence values link “big data” with “model,” which in turn are connected with a multiplicity of other nodes. Performance and impact considerations are central too, reflecting the outcome-oriented nature of these studies. On the right side, keyword co-occurrences indicate a strong presence of AI studies linking big data analytics with capabilities, competitive advantage, or firm performance. Then at the bottom, we find a strong presence of studies that connect firm management and strategy with data mining, analytics, and innovation through AI.

6.5. Mapping central keywords over time

With a further examination of the keywords, we investigate the progression of central focus areas over time. These analyses and subsequent plotting of keywords were performed by algorithms in Citespace. They reveal that the research field has become more diversified in recent years, so we concentrate on multiple keywords in the similar time periods, which become apparent through their overlaps, as we depict in Fig. 10. In particular, the dynamic evolution of keywords indicates a shift in focus, from information and methods (text mining) to more defined applications of AI techniques to marketing problems. The keywords appearing after around 2015 highlight various aspects of AI in marketing, such as its influence on customer satisfaction, WOM, or firm performance. They also signal pertinent challenges, such as the use of big data and analytics for gaining competitive advantage or the importance of building AI capabilities within the firm.

6.6. Authorship cooperation and journal co-citation analysis

Scientific research depends on incremental improvements, so cooperation among researchers is important to advance any field. Collaborations also provide researchers with access to valuable expertise and allow them to share costs, pursue complementary lines of effort, and avoid duplications (Holdren, 2017; Silipo, 2008).

Fig. 11 depicts scientific collaborations among the leading researchers in the field, identifying three prominent researchers in the most central positions: Hein Ruys, Jaesoo Kim, and Sherrie Wei. Their work connects to other major researchers too, including (on the left) Roland Schegg, Paul Phillip, and Maria Manuela Santos Silva and (on the right) Alfonso Palmer, Juan José Montaño, and Albert Sesé. Many of these researchers study uses of AI in tourism marketing.

In addition to researchers, the source journals symbolize the domain. Exploring and reviewing the underlined publication trends among leading journals is likely to significantly help any research institution to identify the core strengths of the intellectual domain and reinforce scientific cooperations. Moreover, the analysis reveals the formation and development of intellectual networks within the knowledge base and provides valuable insights into the journals that have collectively shaped the field. In Fig. 12, the co-citation network among leading journals that published articles on AI in marketing shows the prominence of *Journal of Marketing* and *Journal of Marketing Research*, which cite each other extensively. The *Journal of the Academy of Marketing Science, MIS*

Table 5
Significant publications on AI in marketing in terms of centrality.

Centrality Score	Article
82	McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D., 2012. Big data: the management revolution. *Harvard Business Review,* 90(10), pp.60–68.
69	Chen, H., Chiang, R.H. and Storey, V.C., 2012. Business intelligence and analytics: From big data to big impact. *MIS Quarterly,* 36(4), pp.1165–1188.
59	Bishop, C.M., 1995. *Neural networks for pattern recognition.* Oxford University Press.
56	Barney, J., 1991. Special theory forum the resource-based model of the firm: origins, implications, and prospects. *Journal of Management,* 17(1), pp.97–98.
47	Thieme, R. Jeffrey, Michael Song, and Roger J. Calantone, 2000. Artificial neural network decision support systems for new product development project selection. *Journal of Marketing Research,* 37 (4), 499–507.
47	George, Gerard, Martine R. Haas, and Alex Pentland. Big data and management. *Academy of Management Journal,* 57(2), pp. 321–326.
46	West, P.M., Brockett, P.L. and Golden, L.L., 1997. A comparative analysis of neural networks and statistical methods for predicting consumer choice. *Marketing Science,* 16(4), pp.370–391.
41	Hornik, K. and Kuan, C.M., 1992. Convergence analysis of local feature extraction algorithms. *Neural Networks,* 5(2), pp.229–240.
39	Hruschka, H., 1993. Determining market response functions by neural network modeling: a comparison to econometric techniques. *European Journal of Operational Research,* 66(1), pp.27–35.
37	Krycha, K.A. and Wagner, U., 1999. Applications of artificial neural networks in management science: a survey. *Journal of Retailing and Consumer Services,* 6(4), pp.185–203.

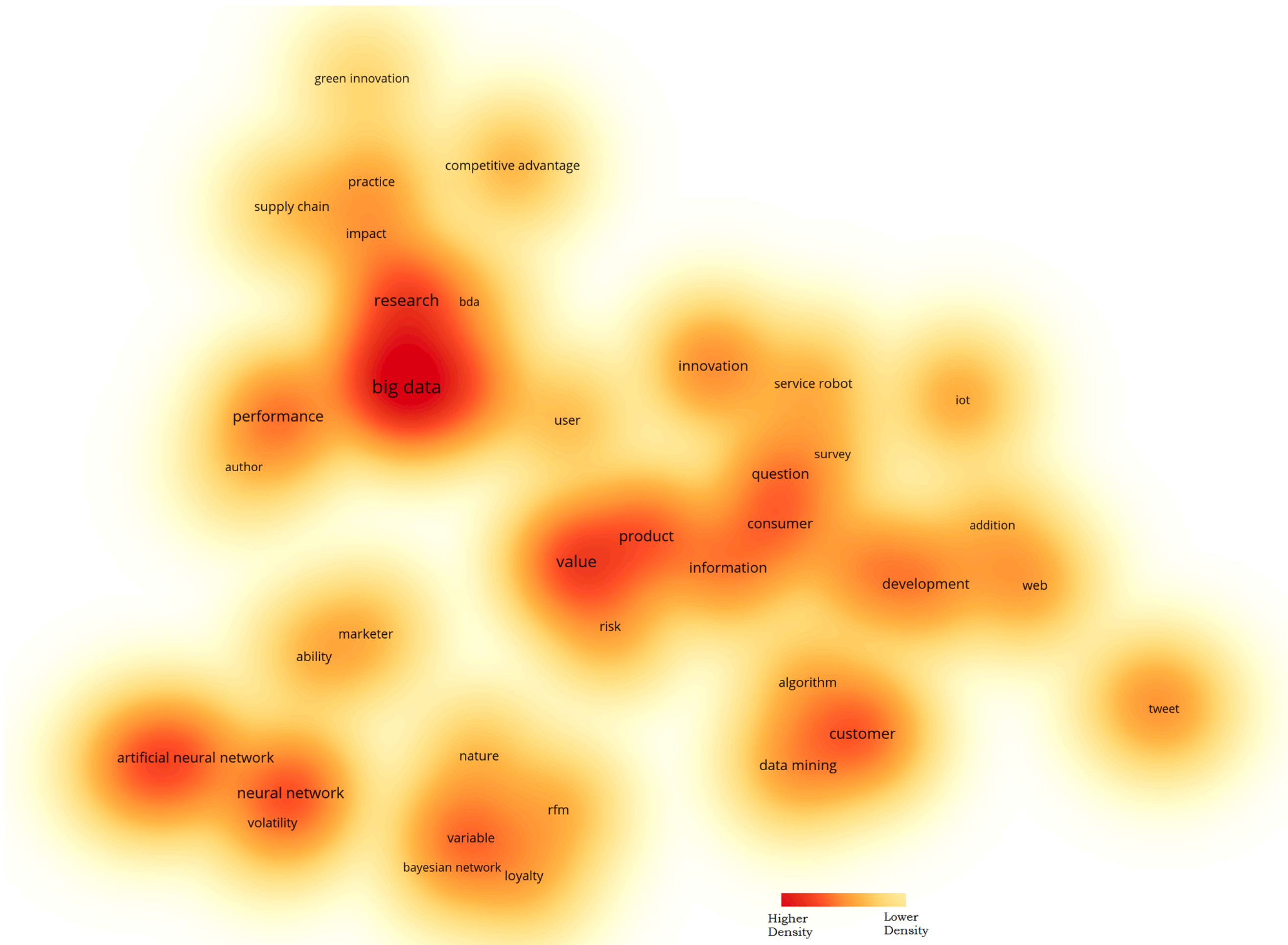


Fig. 8. Density visualization of the prominent keywords.

Quarterly, Harvard Business Review, Journal of Business Research, and *Strategic Management Journal* complement the core of this research domain.

7. Conclusion

7.1. General discussion

This research uses topic modeling in combination with scientometric analysis to perform a novel, systematic, and comprehensive review of AI research in marketing. Unlike traditional review methods, we adopt an algorithm-based advanced methodology; in so doing, we confirm the applicability of topic modeling and scientometric analysis for analyzing business research (Vanhala et al., 2020). With this review of 214 articles published between 1960 and March 2019, we identify ten salient topics, which we propose categorizing into two broad categories, pertaining to either consumer research—understanding consumer sentiments, analyzing customer satisfaction, eWOM-based insights, using AI for brand management, measuring and enhancing customers' loyalty and trust, and using AI to improve customer relationships—or organization and strategy—industrial opportunities of AI, improving market performance, AI and novel services, and AI and strategic marketing. As this topic modeling shows, we can uncover some common content in papers by studying latent topics that are not identifiable at first glance.

Then with a scientometric analysis, we construct knowledge maps of co-citation clusters, landmark publications, conceptual/theoretical bases, and mutual interconnectedness based on the paired presence of concepts within the literature base. Moreover, we detail the evolution in research focus, scientific collaborations among leading researchers, the strengths of the intellectual domain, and cooperative efforts. These analyses provide insights for researchers who want to contribute further, by clarifying the existing core literature base, directions in developments of the research field over time, journals they should look to for guidance, and with whom they might collaborate. For example, in looking at publication outlets, we note that the most prominent marketing journals, such that they are likely to exert more influence within the research community (Vanhala et al., 2020), include *Journal of Business Research*, which has published the most articles on the topic, as well as *Journal of Marketing, Journal of Marketing Research, MIS Quarterly*, and *Journal of the Academy of Marketing Science*.

7.2. Research directions for AI in marketing

To address the challenges and grasp the opportunities of AI for marketing research, we propose research questions for two interrelated, relevant streams within the marketing domain (Dong & Sivakumar, 2017): (1) increase depth and (2) increase breadth.

7.2.1. Increase the depth of AI research

Using AI without understanding its mechanisms is likely to result in detrimental consequences, so endeavors should be made, along different directions, to enrich key constructs and theoretical insights. As Haenlein and Kaplan (2019, p. 11) caution though, "deep learning, a key technique used by most AI systems, is inherently a black box." The lack of transparency regarding how machine learning algorithms work or the profundity with which they may affect organizational and individual

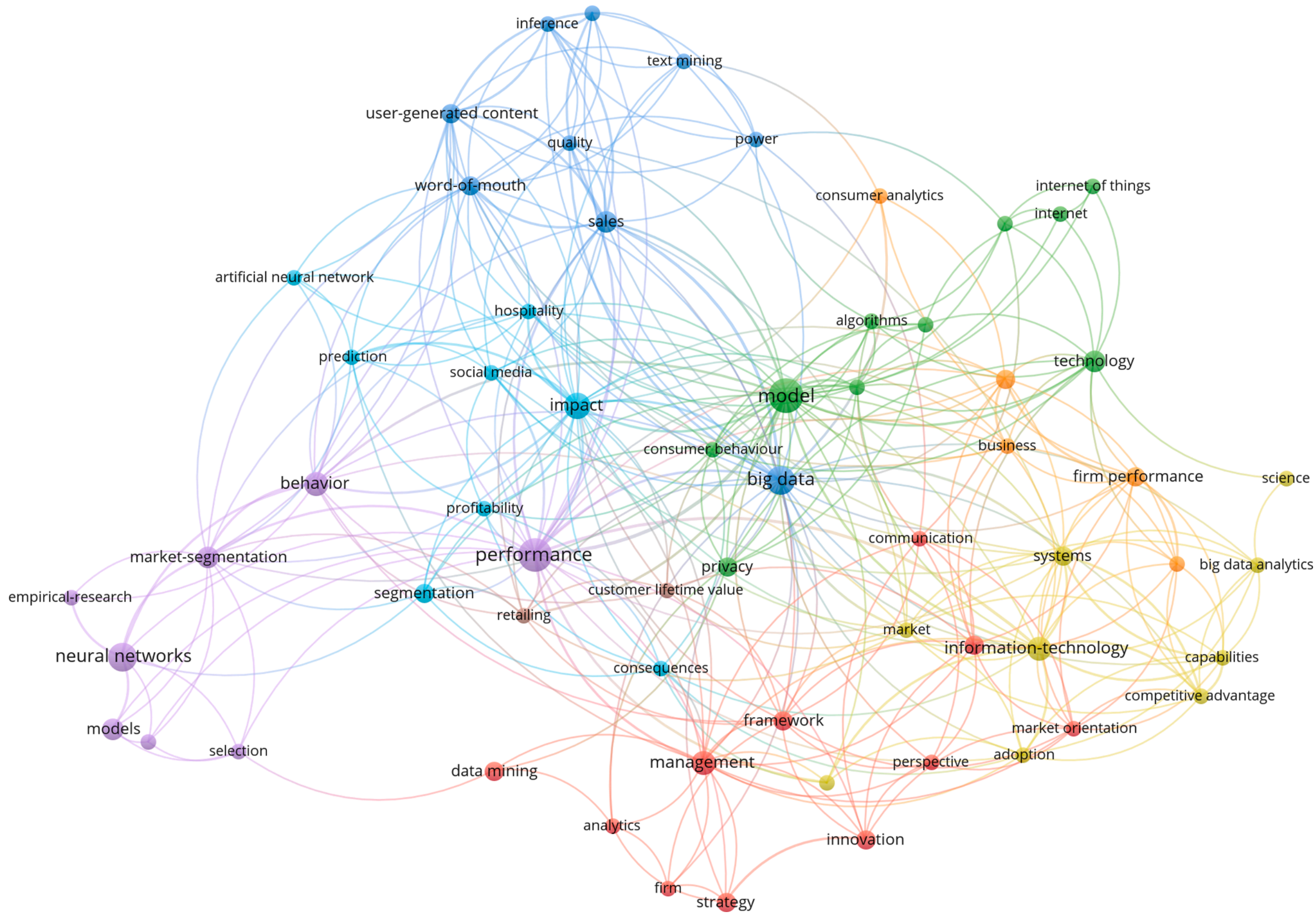


Fig. 9. Keyword co-occurrences in the literature-base on AI in marketing.

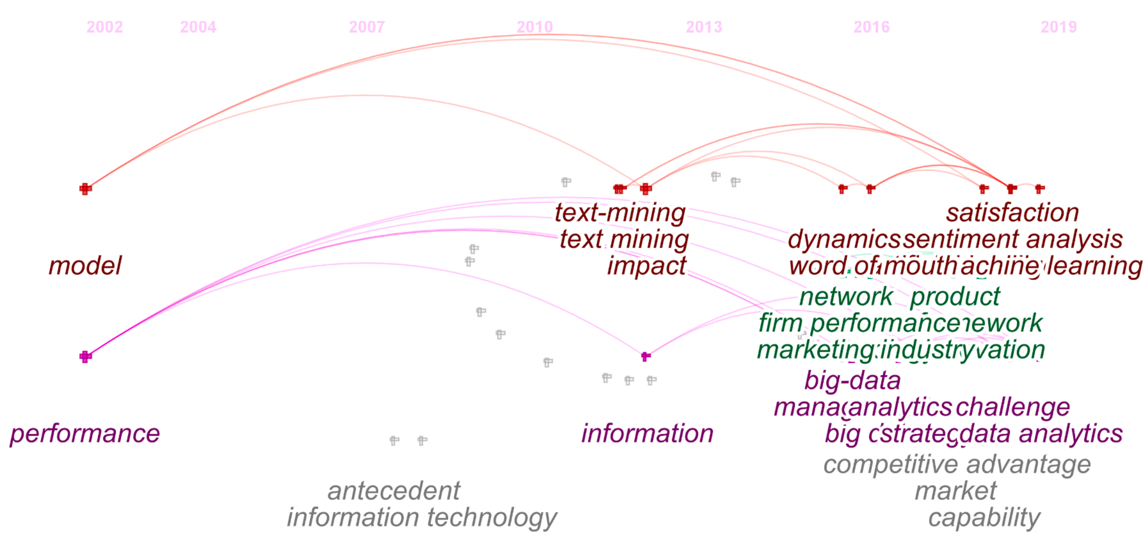


Fig. 10. Temporal mapping of central keywords.

decisions and actions can lead to tactical and strategic mistakes, because managers fail to understand, for example, how the AI systems they rely on work (De Bruyn et al., 2020). Questions worthy of investigation could then include:

- What is the nature and extent of training that marketers should receive on the different technologies and processes of AI?
- What role should marketers take in designing AI-based marketing systems?
- At what point should decisions be automated rather than made by humans?
- Is there an ideal balance between the nature and extent of tasks and activities automated by AI or performed by human marketers?

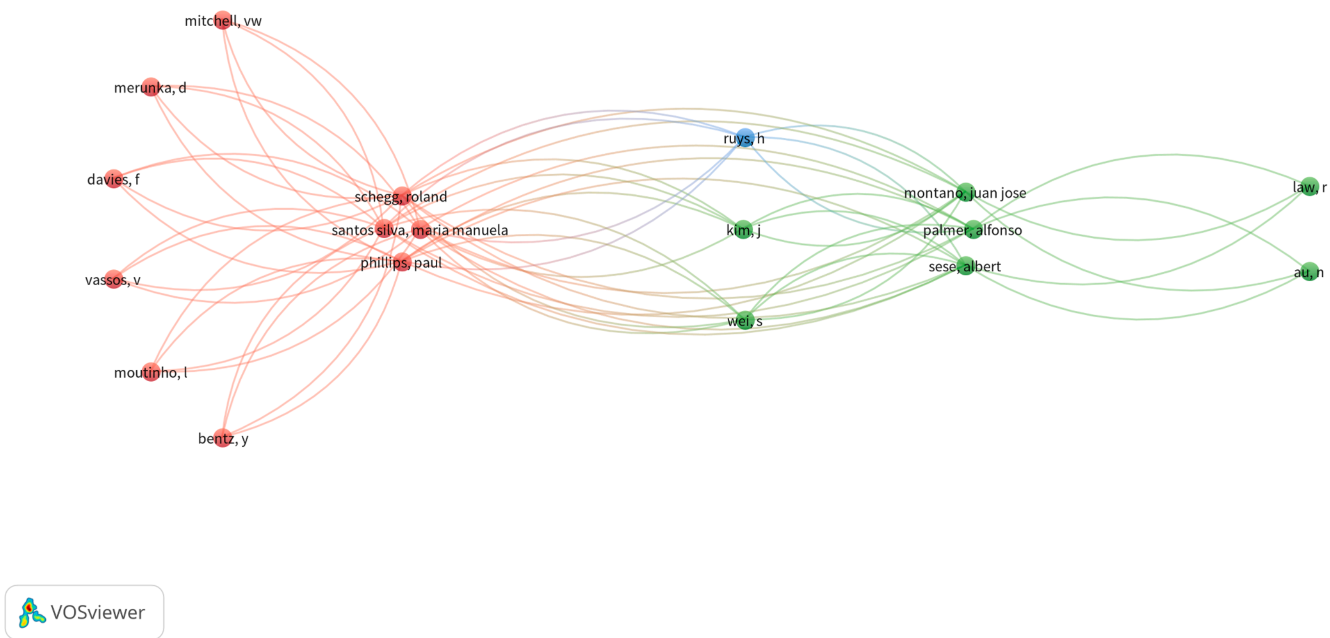


Fig. 11. Co-authorship networks in the literature-base on AI in marketing.

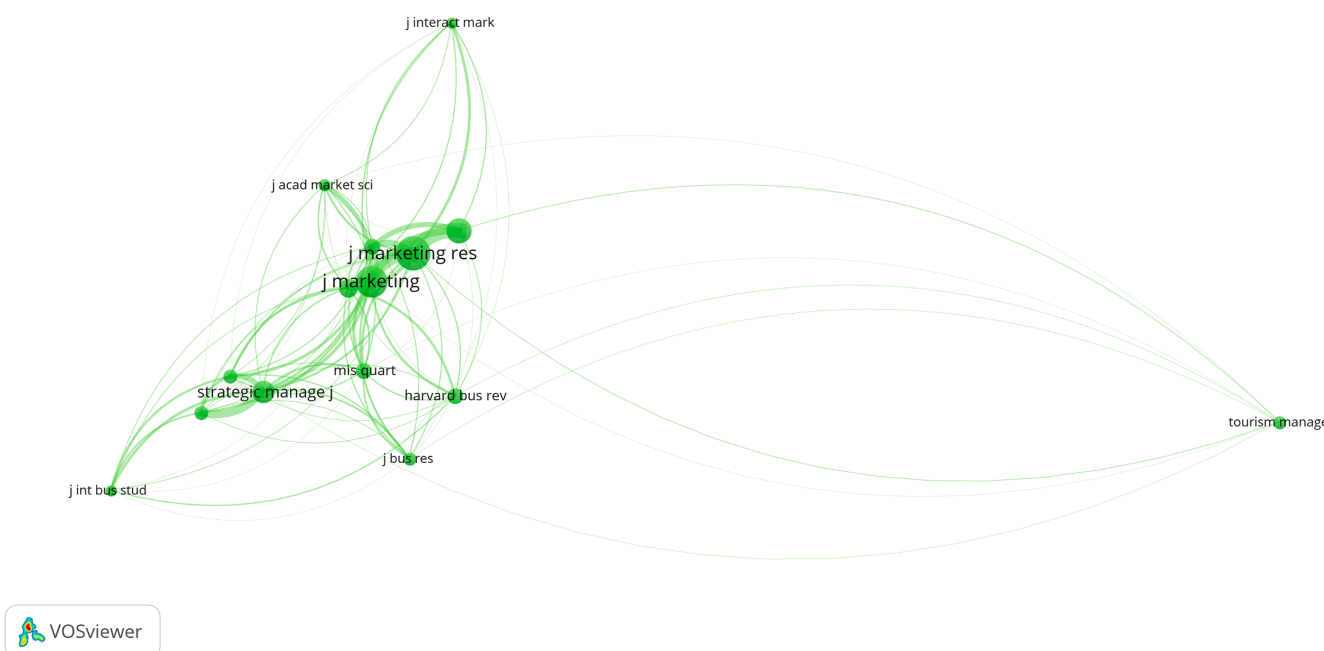


Fig. 12. Co-citations in the literature-base on AI in marketing between the top publishing journals.

As we found (see Table 4), extant studies mainly address how a focal firm can leverage AI to improve its marketing functions and perform marketing tasks, using information, knowledge, and technology. Few studies explore the management of AI networks (Table 4, Fig. 7). That is, we lack a network-wide focus (i.e., the entire network is the level of analysis) that addresses how collaborative, systemic aspects of AI should be managed (Davenport et al., 2020; Randhawa, Wilden, & Hohberger, 2016; Rangaswamy et al., 2020).

According to our topic modeling, we also note the limited discussion of the effects of AI on society in general, despite its strong likely influence on the entire economy (PricewaterhouseCoopers, 2017). In particular, we might reasonably anticipate dramatic changes in the nature and quantity of the workforce as the rise of AI puts jobs of all kinds (including in the marketing profession) in jeopardy (Huang & Rust, 2018). The topic modeling hints at the broad scope of tasks and activities that AI can perform. Yet our scientometric analyses also reveal that current AI research in marketing is concentrated in only a few countries and universities. The digital divide—or the disparity between populations and regions with versus without access to modern information and communication technologies and its effects—is a critical issue that requires marketers to address some urgent questions:

- How can we avoid social discrimination created through the usage of AI?

- How can AI be applied inclusively, to avoid enhancing the wealth gap or allowing wealth to accumulate further with only a few individuals?
- Considering the power of AI to penetrate almost every aspect of society, can it be leveraged to create and capture value within ethical boundaries?

7.2.2. Increase the breadth of AI research

We also call for research to explore connections of AI with other theoretical structures, entities, disciplines, and technological developments. According to our listing of salient topics, we note that marketing studies of AI mainly take an outside-in view. Vast amounts of unstructured data, including consumer usage, review, and response data, are available outside organizational boundaries. Companies should harvest these data and deploy AI to generate meaningful insights, but they also should adopt an inside-out perspective and use AI to perform internal organizational functions and deliver more benefits to customers. Research from this perspective could assess, for example, methods to generate and distribute marketing content automatically through the use of AI. Without the need for human writers or editors, the firm could establish self-sustaining websites that encompass machine learning algorithms. They also might exploit AI for content intelligence, defined as the automated generation of customized content.

In addition to context-based studies, we note the need for contextual expansions. For example, estimates predict that 55% of households will have a smart speaker device by 2022from just 13% in 2018 (BusinessWire, 2020; Forbes, 2020). Such devices integrate series of complex AI technologies: They listen to sound waves and translate them into words using automatic speech recognition; translate the words into definitions using natural language understanding processes; and respond using natural language generation technology. In masking their complex technologies, they provide an easy, nearly frictionless user experience, so revenues earned from shopping via voice comments are predicted to leap to US$40 billion in 2022, up from US$2 billion in 2018 (BusinessWire, 2020; Forbes, 2020). Marketers thus must find ways to take advantage of AI-based smart speakers, as well as for other devices such as wearable accessories.

Current research lags behind business practice in several areas. For example, businesses are using AI for customized pricing, because applications and website bots can leverage predictive analytics by tracking cookies, search histories, and other activity data to recommend real-time pricing. Ride-sharing apps match demand and supply in a specific location, so these firms already offer highly customized prices to end-users and payments to drivers (Rangaswamy et al., 2020). Research that addresses these uses of AI for pricing decisions thus would be of great benefit to both academics and practitioners.

7.3. Limitations

By combining topic modeling with scientometric analyses, we avoid subjective biases that are often associated with non-systematic literature reviews, expert surveys, and opinion pieces. However, our findings are inevitably influenced by our selection of keywords and restricted to the coverage of the WoS database. The studies we examine offer a representation of existing research (published and in-press articles); we do not include ongoing and unpublished knowledge, such as contained in articles under review. Despite these shortcomings, this study helps clarify the structure and development of AI research in marketing and suggests directions for further research in this critical field.

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