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Artificial intelligence in marketing: Systematic review and future research direction

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A R T I C L E I N F O

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A B S T R A C T

Disruptive technologies such as the internet of things, big data analytics, blockchain, and artificial intelligence have changed the ways businesses operate. Of all the disruptive technologies, artificial intelligence (AI) is the latest technological disruptor and holds immense marketing transformation potential. Practitioners worldwide are trying to figure out the best fit AI solutions for their marketing functions. However, a systematic literature review can highlight the importance of artificial intelligence (AI) in marketing and chart future research directions. The present study aims to offer a comprehensive review of AI in marketing using bibliometric, conceptual and intellectual network analysis of extant literature published between 1982 and 2020. A comprehensive review of one thousand five hundred and eighty papers helped to identify the scientific actors' performance like most relevant authors and most relevant sources. Furthermore, co-citation and co-occurrence analysis offered the conceptual and intellectual network. Data clustering using the Louvain algorithm helped identify research sub-themes and future research directions to expand AI in marketing.

Summary Statement of Contribution

Artificial Intelligence (AI) in Marketing has gained momentum due to its practical significance in present and future business. Due to the wider scope and voluminous coverage of research studies on AI in marketing, the meta-synthesis of exiting studies for identifying future research direction is extremely important. Extant literature attempted the systematic literature review, but existing reviews are descriptive, and latent intellectual network structure remained unexplored. Present study used bibliometric analysis, conceptual network analysis, and intellectual network analysis to identify research subthemes, trending topics and future research directions.

1. Introduction

Technological disruptions such as artificial intelligence (AI), internet of things (IoT), big data analytics (BDA) have offered digital solutions for attracting and maintaining the customer base (Anshari, Almunawar, Lim, & Al-Mudimigh, 2018; Bolton et al., 2018). Emerging technologies provide a competitive advantage (Rouhani et al., 2016; Spring et al., 2017) by facilitating the customers' product and service offerings (Balaji & Roy, 2017; Khanagha et al., 2017; Liao, 2015). In the current business scenario, the cut-throat competition and technological disruptions have changed the way organizations operate (Gans, 2016). Globally customer-centric approach focused on customer needs plays a pivotal role in organizational growth (Vetterli, Uebernickel, Brenner, Petrie, & Stermann, 2016). Artificial intelligence (AI) is a widely used emerging technology that helps organizations track real-time data to analyze and respond swiftly to customer requirements (Wirth, 2018). AI offers consumer insight on consumer behavior essential for customer attraction and customer retention. AI incites the customer's next move and redefines the overall experience (Tjepkema, 2019). AI tools are useful to deduce customer expectations and navigate the future path (Shabbir, 2015).

Artificial Intelligence find its applications in different context in today's business scenario. Practitioners and academicians believe that Artificial Intelligence is the future of our society. With the advancement of technology, the world has become a web of interconnected networks. The technology implementation lead to investment in Artificial Intelligence (AI) for big data analytics to generate market intelligence. Artificial Intelligence applications are not limited to only marketing; rather, it is widely used in other sectors such as medical, e-commerce business, education, law, and manufacturing. AI is continuously getting implemented to benefit many different industries. As the organizations move forward towards Industry 4.0, Artificial Intelligence & other emerging technologies are also evolving parallelly. However, the implementation of AI in all sectors has not been possible due to many constraints, but

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scientists are working on systems that cater to the theory of mind and self-awareness of the artificially intelligent systems.

Nowadays the people interact with some form of AI in daily activities. For example, the user enjoys the automatic e-mail filtering feature. In the smartphone, the user may probably fill out a calendar with Siri, Cortana, or Bixby. The user of the new vehicle gets assisted by a while driving. Artificial Intelligence can automate the business process, learn insights from past data, and generate consumer and market insights through the program-based algorithm (Davenport et al 2020). Technologies like Machine Learning (ML), Deep Learning, and Natural Language Processing (NLP) train machines to handle big data for the generation of market intelligence (Davenport et al 2020). As the adoption of AI in marketing is in nascent stages, there is a dearth of systematic literature review exhibiting the in-depth research pattern in the AI-driven consumer market and lead to research questions like

RQ1: What are the applications of AI in Marketing?

RQ2: How marketing can optimally utilize the AI technologies for maximizing customer satisfaction, market share and profitability?

RQ3: What are the trending topics and future research directions for the adoption of AI in Marketing?

This paper attempts to fill that research gap through a systematic review of literature on AI in the marketing research domain. Bibliometric analysis of more than 1500 articles (published between 1982 and 2020) offered scientific actors' performance like most relevant authors, most relevant sources etc. Co-citation and co-occurrence analysis based on the Louvain algorithm helped to map the research domain's conceptual and intellectual structure.

In the subsequent sections, literature review, research methodology, findings, discussion and conclusion are presented.

2. Literature review

Unlike human intelligence, artificial intelligence (AI) is the intelligence demonstrated by the machines. A system of intelligent agent machines that perceives the environment to successfully achieve its goal represent the artificial intelligence. According to Russel and Norvig (2016), artificial intelligence describes machines (computers) that simulate cognitive and affective functions of human mind. The development of Artificial intelligence is phenomenal and experts have worked tirelessly to advance AI concepts over the few decades. The work led to some major innovations like big data analytics and machine learning applications in myriad sectors and context.

The term Artificial Intelligent generally leads people to think only about automated robots who work for humans because the people have only seen the human-machine interaction in the movies or any shows through robots only. Artificial Intelligence applies to any kind the machine that needs to think like a human resulting in continuous learning and problem-solving. These are the features of AI that make it unique. Sometimes people find a task boring or dull, which is repetitive. However, with the help of a machine, people never have to experience a similar job as boring. An artificially intelligent system does repetitive jobs for humans continuously.

Data ingestion is a very important feature of artificial intelligence. Artificially intelligent systems work with huge amounts of data. The artificial intelligence system collects data according to requirement and analyze the huge chunks of data. There is a huge amount of data that organizations like google, amazon handle & that is impossible to analyze by humans. Also, an artificially intelligent system stores multiple information about multiple people, multiple machines from multiple sources. All of this appears on the system asynchronously or simultaneously.

AI-enabled systems are designed to observe and react to their surroundings. They perceive the environment and take actions accordingly and keep in mind the situations that might come up soon. For example, AI, with the help of historical data, can predict the breakdown time of a machine. It can alert us for the action beforehand.

2.1. Advantage of machine learning over other technologies

Many technologies may do repeated work, but they can't think independently. They lack to think outside their code. On the contrary, Machine learning is a subset of AI that aims to give machines the ability to learn a task without pre-existing code. Here machines are fed with some of the problems and examples through which machines learn for certain tasks. As they go through these problems & examples, machines learn and adapt their strategy to independently execute the activities. For example, an image-recognition machine may be given millions of pictures to analyze. After going through endless permutations, the machine acquires the ability to recognize patterns, shapes, faces, and more.

In today's scenario, the machine is only learning for the specific repeated task, but the machines are trained to learn more than just a specific task. The AI experts are working to make the machine able to take what it has learned from analyzing photographs and using that knowledge to analyze different data sets. Data scientists & programmers are formulating general-purpose learning algorithms that help machines learn more than just one specific task.

2.2. Principle behind working of artificial intelligence

Artificial intelligence is that human intelligence can be transferred to machines to execute tasks from the simplest to the most complex. The objective of artificial intelligence is to learn, do reasoning & execute the activities. As technology moves forward, previous standards that explain artificial intelligence become outdated. There are three basic concepts behind Artificial Intelligence. These basic concepts are machine learning, deep learning, and neural networks. These concepts are leading to further development of data mining, natural language processing, and driving software. While AI and machine learning may seem like interchangeable terms, AI is usually considered the broader term, with machine learning and the other two AI concepts a subset of it.

The mechanism of Deep learning is based on the principle of artificial neural networks. It imitates neurons or brain cells. Artificial neural networks were inspired by things we find in our biology. The neural net models use math and computer science principles to mimic the human brain processes, allowing for more learning & command to act. An artificial neural network integrates the processes of densely interconnected brain cells, but instead of being built from biology, these neurons, or nodes, are built from human-made code.

Neural networks contain three layers: an input layer, a hidden layer, and an output layer. These layers contain thousands, sometimes million nodes. AI imitates human minds through the concepts of neural networks. It thinks the way a human thinks & acts accordingly to solve the problems. This is the uniqueness of AI. AI imitates human brain to interpret the environment & act accordingly.

2.3. Use of artificial intelligence in marketing

The authors undertook the literature review to comprehend the extent of research on enhancing customer experiences through AI. Gacanin and Wagner (2019) described the implementation challenges of autonomous customer experience management (CEM). The paper also narrated how the intelligence network and critical business value driver were established through AI and ML. Customer experience improved through AI-driven chatbot with Natural Language Processing (NLP) (Nguyen and Sidorova, 2018). AI and ML algorithms enabled efficient data processing, which allows us to formulate the correct decision (Maxwell et al., 2011). Application of AI is required to analyze customer habits, purchases, likings, disliking, etc. (Chatterjee et al., 2019). Customer Relationship Management (CRM) functions benefited through Artificial Intelligence User Interface (AIUI) (Seranmadevi & Kumar, 2019). AI and IoT converted traditional retail stores to smart retail stores. The smart retail stores elevated customer experience and ease of shopping, and better supply chain (Sujata et al., 2019). Besides brick-and-

Table 1
A literature review on artificial intelligence in marketing.

Author(s)	Study based on	Findings
Gacanic and Wagner (2019)	Autonomous CEM	Establishment of critical business drivers through AI and ML
Nguyen and Sidorova (2018)	Enhancement of customer experience through AI	Customer experience enhanced through AI-driven chatbot
Maxwell et al. (2011)	Data processing through AI and ML algorithm	Correct the marketing decision made through AI and ML algorithm-based data processing
Chatterjee et al. (2019)	Application of AI in marketing	Based on the AI application analysis of customer habits, purchases
Seranmadevi & Kumar (2019)	AIUI in CRM	CRM functions evolution through AIUI
Sujata et al., (2019)	Smart Retail stores	Customer experience enhancement, world-class SCM through a smart retail store
Sha and Rajeswari (2019)	Advanced AI in e-commerce	Advanced AI-enabled machine could be able to track five human senses and improved e-commerce business

mortar stores, AI guides the online businesses also. Sha and Rajeswari (2019) described the advancement of AI and demonstrated the AI-supported machine, which can track the five senses (sight, hearing, taste, smell and touch) of humans. The result showed a better consumer-brand association and product-brand association in the e-commerce business. A summary of some of the interesting research studies is presented in Table 1.

2.3.1. Use of artificial intelligence in strategy and planning

Artificial intelligence can support marketers in strategy and planning marketing activities by helping in segmentation, targeting, and positioning (STP). Besides STP, AI can help marketers in visioning strategic orientation of firm (Huang & Rust, 2017). Text mining and machine learning algorithms can be applied in sectors like banking and finance, art marketing, retail and tourism for identification of profitable customer segments (Dekimpe, 2020; Netzer et al., 2019; Pitt et al., 2020; Valls et al., 2018). A combination of data optimization techniques, machine learning and causal forests can narrow down the targeted customers also (Chen et al., 2020; Simester et al., 2020).

2.3.2. Use of artificial intelligence in product management

Artificial intelligence-based marketing analytics tool can gauge the suitability of product design to the customer needs and resultant customer satisfaction (Dekimpe, 2020). Topic modeling adds to the system capabilities to service innovation and designs (Antons & Breidbach, 2018). Preference weight assigned to product attributes during product search help the marketers to understand product recommender system and align marketing strategies for meaningful product management (Dzyabura & Hauser, 2019). Deep learning can personalize the point of interest recommendation and helps to explore new places (Guo et al., 2018). Artificial intelligence offers capabilities to customize offerings to suit to the customer needs (Kumar et al., 2019).

2.3.3. Use of artificial intelligence in pricing management

Pricing involves factoring of multiple aspects in finalization of price and it is a calculation intensive job. Real time price variation based on fluctuating demand adds to the complexity of pricing task. Artificial intelligence based multiarmed bandit algorithm can dynamically adjust price in real time scenario (Misra et al., 2019). In the frequently changing pricing scenario like e-commerce portal, Bayesian inference in machine learning algorithm can quickly adjust the price points to match the competitor's price (Bauer & Jannach, 2018). According to Dekimpe (2020), best response pricing algorithms encapsulate customer choices, competitor strategies and supply network to optimize dynamic pricing.

2.3.4. Use of artificial intelligence in place management

Product access and product availability are essential component of marketing mix for heightened customer satisfaction. Product distribution relies on networked relationship, logistics, inventory management, warehousing and transportation problems, which is largely mechanical and repetitive in nature. Artificial intelligence is the perfect solution in the case of place management by offering cobots for packaging, drones for delivery, IoT for order tracking and order refilling (Huang & Rust, 2020). Standardization and mechanization of distribution process adds convenience to both suppliers and customers. Besides utility in distribution management, AI also offers customer engagement opportunities in service context. Service robots programmed with emotional AI codes are handy in surface acting (Wirtz et al., 2018). Embodied robots greet and engage with customers, but human elements need to complement the service environment for customer delight. Automation of service process with AI offers additional opportunity for performance and productivity improvement (Huang & Rust, 2018).

2.3.5. Use of artificial intelligence in promotion management

Promotion management entail media planning, media scheduling, advertising campaign management, search engine optimization etc. Promotion tactics are transforming from physical to phygital. Digital marketing and social media campaigns made an inroad due to digital transformation across the globe. In the changed technological world, customer decide the content, place, and timing. AI offers personalization and customization of message as per the customer profile and likings (Huang & Rust, 2020). Content analytics can optimize value and message effectiveness. Customer likings and disliking can be tracked in real time with emotive AI algorithms. Netnography on social media content offers new avenues for marketers to align their marketing strategies as per the customer likings (Tripathi & Verma, 2018; Verma, 2014; Verma & Yadav, 2020).

3. Methodology

We used Rowley and Slack's (2004) guidelines for conducting the literature review. Methodologically, the literature review used a five-stage process described in the following sections. Comprehensive review protocols helped in the identification of research themes and future research directions.

3.1. Selection of bibliometric databases

Scopus and Web of Science (WoS) are the two most reputed bibliometric databases. We explored both Scopus and Web of Science (WoS) databases to search the relevant literature. According to Yong-Hak (2013), Scopus had broader coverage, and it includes more than 20,000 peer-reviewed journals from different publishers (Fahimnia et al., 2015). Due to its wider coverage, we preferred Scopus for data collection. Scopus offered advanced search filters and data analysis grids for better data management.

3.2. Defining keywords (search strategy)

The initial search string included words like "marketing" and "artificial intelligence." Synonyms used for artificial intelligence like machine learning, deep learning, natural language processing, etc., are used with boolean operators like "OR" to get the universal set of papers. Boolean operator "AND" is used to get the intersection set of paper covering marketing and artificial intelligence.

Table 2
Descriptive statistics.

Main information	Description	Results
Articles	Documents	1580
Sources (Journals, Books, etc.)	The frequency distribution of Sources	710
Keywords Plus (ID)	Keywords Plus (ID)	5780
Author's Keywords (DE)	Total number of Keywords (DE)	5062
Average citations per documents	The average number of citations in each document	12.42
Authors	Total number of Authors	3991
Author Appearances	Author Appearances	4631
Multi-authored	Authors of multi-authored documents	3779
Single-authored documents	Single-authored documents	224
Documents per Author	Documents per Author	0.396
Authors per Document	Number of authors per Document	2.53
Co-Authors	Co-Authors per Documents	2.93
Collaboration Index	Collaboration Index number	2.79

Table 3
Most Relevant sources.

Source	No. of papers pub.	H-index	G-index	Total no. of citations
Expert Systems with Applications	87	27	48	2574
Journal of Business Research	27	12	20	445
Knowledge-Based Systems	20	12	20	610
Industrial Marketing Management	17	10	17	324
European Journal of Operational Research	16	11	16	421
Information Sciences	16	8	16	305

3.3. Refining the initial results (Inclusion and exclusion criteria)

Inclusion and exclusion criteria are applied to the search results. With the help of inclusion and exclusion criteria, delimitation helped in the extraction of the most relevant articles for the literature review. To achieve the research objective, the search results limits to only articles published in journals as they represent "certified knowledge" (Ramos-Rodríguez and Ruiz-Navarro, 2004). Conference papers, book chapters, commentaries, erratum etc., were excluded from the search results.

3.4. Data analysis plan

The bibliometric analysis of data was carried out using R-software for performance analysis of scientific actors like most relevant authors and most relevant sources. The content analysis and performance analysis of each scientific actor offered the intellectual structure of the research domain. Two researchers analyzed the Scopus data for inter-rater validity.

Data analysis is structured in three stages. Stage 1 data analysis focused on scientific actors' performance like most relevant sources and most relevant authors in the research domain. Bibliometric analysis based on total citations and citation index helped in the performance evaluation of scientific actors. Stage 2 analysis used co-occurrence and co-citation analysis for conceptual and intellectual network analysis. According to Chen et al. (2010), research papers' co-citation network indicates the intellectual structure, concepts co-citation network indicates conceptual structure, and the authors' co-citation network indicates the social structure of the research domain. Stage 3 analysis focused on emerging trends and future research directions of AI in Marketing.

3.5. Identification of research gaps and future research directions

The articles relating to artificial intelligence in marketing were reviewed to understand the theoretical evolution, methodological evolution, and emerging research themes. Thematic coding is used for the qualitative analysis of data. Thematic coding is a form of qualitative analysis that involves recording or identifying passages of text or images linked by a common theme or idea, allowing data to index into categories for the development of the thematic framework (Gibbs, 2007). An in-depth review of research papers in each theme offered research gap insights and helped chart future research directions. Research gaps are translated into research questions that future researchers can embark on to solve.

4. Findings

4.1. Descriptive statistics of bibliographic collection

A total of 1580 documents (1523 articles and 57 reviews) have been published to date on this specific topic in 710 numbers of prominent journals. 5780 number of keywords have been used to date in this topic, and authors have used 5062 keywords to date. Table 2 presents the descriptive statistics of extant research done on artificial intelligence in marketing. The research data has displayed that the average engagement of authors for each paper is 2.79 (collaboration Index)

4.2. Performance of scientific actors

4.2.1. Most relevant sources

Table 3 present the five most relevant sources based on the maximum number of articles published in different journals. Most of the papers on artificial intelligence in Marketing have been published in Expert System with Application. The number of articles published in the next two most relevant journals viz. Journal of Business Research and Knowledge-Based Systems, are far behind from Expert System with Application. Further, to understand the most influential source, the top five most relevant sources were compared on H-index and G-index. Once again, an expert system with applications topped the chart with both the highest H-Index and G-Index. Even the total number of citations is maximum for an expert system with an application. In terms of all indicators, the expert system with applications is the most relevant source.

4.2.2. Most relevant authors

Table 4 presents the five most relevant authors identified based on the maximum number of articles published, total citations and citation indexes (H-Index and G-Index). Liu Y has secured the top rank among all the researchers with 9 article publications. The other two researchers Chen Y and Liu J have also shown their interest in the uses of AI technology in the marketing domain. Further, the author impact is assessed

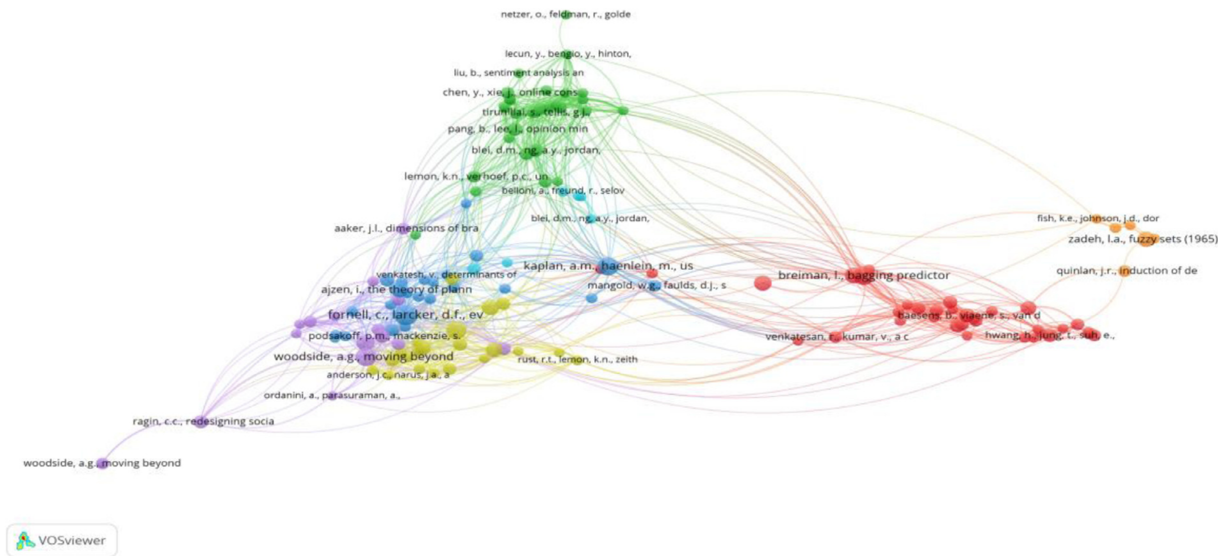

Fig. 1. Co-citation analysis.

Table 4
Most Relevant authors.

Author	h_index	g_index	TC	NP	PY_start
Liu Y	5	9	97	9	2010
Chen Y	5	8	100	8	2010
Liu J	4	8	307	8	2013
Casillas J	7	7	203	7	2009
Chen G	5	7	158	7	2009
Li S	3	7	51	7	2010
Zhang C	4	6	40	7	2014

with the help of total citations (TC), number of articles published (NP), publishing years (PY_start) and citation indexes (g and h indexes). Liu Y has an h-index 5 with TC as 97 whereas, Casillas J has an h-index 7 with 203 TC. Casillas J has more citation records than Liu Y. It is evident from Table 4 that the citation record and h-impact both are independent. Research on a specific topic or a specific sector could impact more, whereas research work might get less citation.

4.3. Intellectual structure

Co-citation analysis offered the intellectual structure of the research domain. The research domain is classified in different clusters with the help of between centrality index computation. Fig. 1 presents the co-citation network analysis. The cluster was prepared based on the strong relationships among articles. Due to many papers in a cluster, the authors have selected only a few with the most citation. The author has selected a total of five clusters. In each cluster, the number of papers varied from two to five. They then studied and discussed the research focus & the suggestions of each cluster.

In cluster one, authors mainly focused on the trust factor that directly impacts selling and distribution in both manufacturing and service organizations. The authors discussed that trust leads to long-term relationships between buyer & supplier, leading to counter-market uncertainty. The authors propose here to continue the relationship & trust between buyer & supplier irrespective of the industry segment to get a competitive advantage. The authors suggest that the research be done in making a marketing model considering the relationship in the future.

In cluster two, the authors discussed the linkages between market orientation & business performance. The author has also discussed how the market is evolving towards customer-centricity. The focus is also shifting to intangible areas such as skills, knowledge & interactions. The author has given future research directions to address the effects of additional factors on market orientation & the relation between market orientation & market share.

In cluster three, the author describes the value creation for the customer. To make long term value to customers get a competitive advantage, the organization prepares structural equation models based on theoretical-methodological & statistical analysis. There is a tremendous opportunity to apply those concepts to add more value, especially in the retail sector areas.

In cluster four, the authors discussed the benefits of data science in various fields such as finance, marketing, consumer research, and management. The authors also deliberated about the role of typological theory on cause-effect relationships. The authors suggested future research work on predictive validity, not just on the fit validity, to address the changing business environment issues.

Cluster five discusses consumer sentiment & word of mouth in online platforms. The data captured through online platforms can be used for dynamic analysis of an organization. This data will lead the organizations to take measures to get a competitive advantage in the market. The studies propose a framework to capture user-generated data. The authors propose to use the data not only from product reviews but also from textual communications.

4.4. Trending topics

Fig. 2 present trend analysis depicting the overall changes in the research topic throughout the change in time. If we divide the whole trend into three phases, the beginning phase shows a basic understanding of the research topic. The researchers were keen to draw the initial picture with basic research understanding. The research topic was evolved once it moves towards the middle phase of the trend. in the last phase from 2017 to 2019, the researchers moved towards emerging technologies inclusion in their work such as Big data, Neural Networking, Machine learning and many more.

According to Camberia (2016), emotion is pivotal for understanding human preference and emotion processing through sentiment analysis, using artificial intelligence can detect consumer polarity. Ever-increasing social network proliferation mandates computational algorithms to make sense of big data and provide deep learning of polarizing consumer sentiments. User-generated content on social networking sites provides deep consumer insights for improved decision-making (Tripathy et al., 2016).

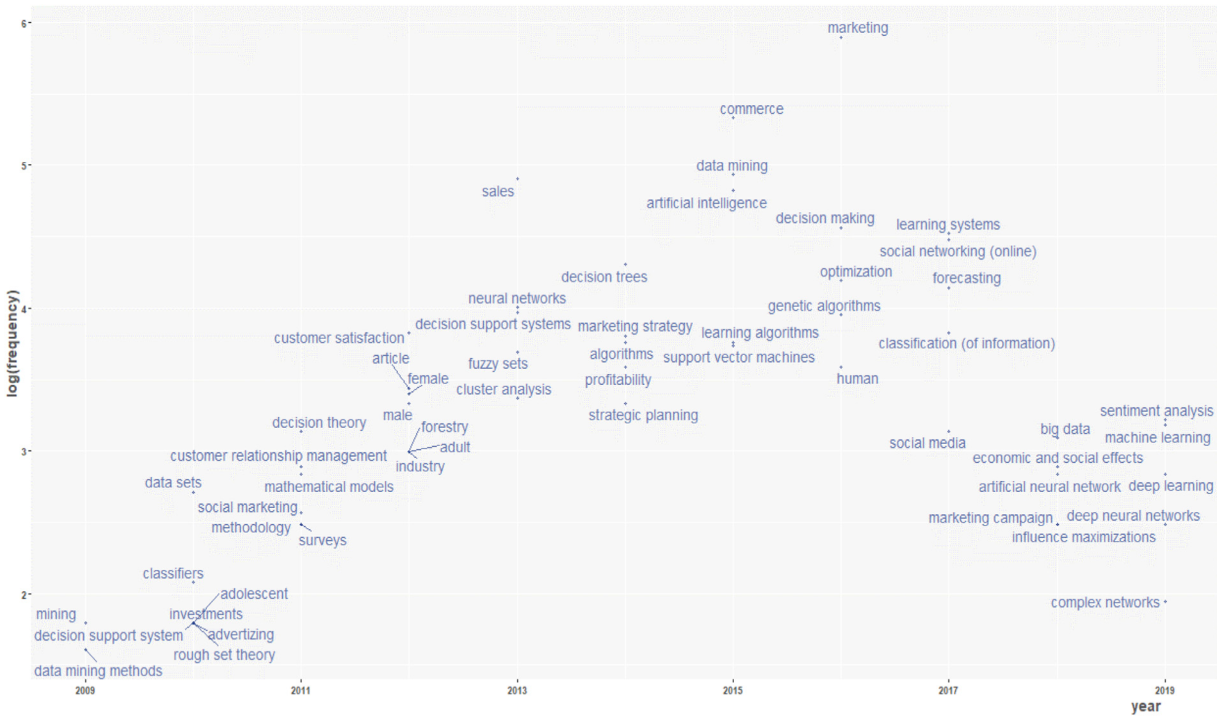

Fig. 2. Trend topics.

Zhang et al. (2016) developed an optimization framework for analyzing object-level video advertising. Deep convolutional neural network based on face features helps to recognize human genders, and heuristics algorithm solves the optimization problem (Zhang et al., 2016). To make artificial intelligence more realistic, computational intelligence must incorporate human language, reasoning and emotions. Poria et al. (2015) combined computational intelligence techniques with linguistic and emotive algorithms via natural language for polarity detection in big social data. The flow of sentiments via contextual route and content route decipher the realistic scenario and portray the dynamic polarity influence on consumer behavior. Wuenderlich et al. (2015) studied smart services via intelligent systems based on real-time data and continuous communication. The value generated from smart services depends on autonomous decision making and object-oriented embeddedness. Giatsoglou et al. (2017) also emphasized sentiment analysis and opinion mining for deeper consumer insights. Textual snippets in different languages are used as vectors for polarity determination to represent high and weak inflection language groups.

4.5. Future research directions

Semantic knowledge and machine learning for deeper consumer insights will offer future researchers new strategic imperatives (Camberia, 2016). Psychologically driven and brain-inspired reasoning algorithms would further improve the predictability of consumer behavior. Psychological theories addressing the cognitive and affective needs of consumers ensembled with engineering tools will help design intelligent sentiment mining systems. Hybrid machine learning techniques will help in better sentiment classification in the future (Tripathy et al., 2016). Optimization models based on existing marketing theories will boost the applicability of AI in marketing (Zhang et al., 2016).

Overt and covert use of emotional expressions on social media adds to predicted behavior's complexity and accuracy. Linguistic patterns for deep learning may help to detect the sarcasm and may improve the sentiment predictability. Development of micro text and anaphora resolution for solving dynamic sentiment analysis would further enhance future researchers' capabilities (Poria et al., 2015). Co-creation of knowledge-based systems improves market acceptability, and future researchers should try to create collaborative market intelligence (Wunderlich et al., 2015). Future researchers should work on high inflection languages and consider emotional lexicons for big data sentiment analysis like Twitter datasets (Giatsoglou et al., 2017).

5. Conclusion

It is no longer a debate that companies who provides great customer experiences will be winners in the Fourth Industrial Revolution — where intelligence will reign supreme. The Fourth Industrial Revolution has been conceptualizing the company to have integrated data about customers and products across all channels and products, using that data to understand better its end customer experience and visibility across all functional areas. In this context, AI and ML have played a crucial role in big data analytics to anticipate and provide guided experiences to meet customer expectations. Through this research, the authors provided a holistic view of using AI to enhance customer experience. Leveraging AI and predictive analytics is the key to offering customer experiences that builds advocacy and customers for life. Event-based architectures combined with AI and predictive analytics is the future. There is no end state, but it is a journey all companies must begin as we enter the Fourth Industrial Revolution.

Disruptive technologies such as internet of things, big data analytics, blockchain, and artificial intelligence have changed the ways businesses operate. Of all the disruptive technologies, artificial intelligence (AI) is the latest technological disruptor and holds immense potential for manufacturing, pharmaceuticals, healthcare, agriculture, logistics, and digital marketing. Many practitioners and academicians worldwide are trying to figure out the best fit AI solutions that their organizations can utilize. However, there is a lack of bibliometric reporting that exhibit detailed research pattern of AI in marketing. Therefore, this study aims to aggregate the research studies about AI in marketing using bibliometric analysis and co-citation analysis.

A five-step methodology for the systematic literature review suggested by Costa et al. (2017) was used in this study. Initially, research terms were defined scientifically along with Boolean operators, followed by a detailed search procedure penned down. Data was collected from the SCOPUS database and saved in BibTeX format and .csv for further analysis. Bibliometric analysis was done for the most relevant authors' descriptive analysis, most frequently used keywords and most relevant research papers. Intellectual structure synthesis was done with the help of co-citation analysis.

The bibliometric analysis includes descriptive statistics of research papers collection. Only articles and review papers were considered for bibliometric analysis. The annual scientific production trend graph indicated the phenomenal growth in interest for artificial intelligence in marketing. In 2009, 99 articles were published, while in 2019, it increased to 311. Bibliometric analysis for most relevant source showed expert system with application has published maximum articles (87) on the subject. This journal has the highest impact, with an H-index score of 27. Liu Y was the most relevant authors with a total of 9 article publications and the highest h-index.

Conceptual network analysis was done with the help of trend topics analysis and document analysis. Day's (2011) paper on closing the marketing gap with artificial intelligence got the highest citation (302) with an average of 34 citations per year. But some papers published in a later stage are performing better than the top of the list. For instance, Camberia's (2016) paper on affective computing and sentiment analysis has already received 292 citations merely in 3 years, with an average of 73 citations per year. Trending topics were divided into three phases. The initial phase focused on a basic understanding of the research topic. It evolved through the second phase with applications in different contexts, followed by the last phase that emphasized emerging technologies, including Big data, Neural Networking, and Machine learning, for better predictive analytics.

Co-citation analysis was done to understand the intellectual structure of the research domain. The research domain is classified in different clusters with the help of between centrality index computation. In cluster one, authors mainly focused on the trust factor that directly impacted the organization's performance and emphasized the marketing model based on relationships. In cluster two, researchers discussed the linkages between market orientation & business performance. In cluster three, the author used structural equation models based on a theoretical methodology to explore value co-creation with customers. In cluster four, the authors discussed the benefits of data science in various fields such as finance, marketing, consumer research, and management. The authors also deliberated about the role of typological theory on cause-effect relationships. Cluster five focused on emerging technologies and techniques like consumer sentiment for consumer insight and dynamic analysis of an organization. The studies propose a framework to capture user-generated data.

To draw attention to emerging trends and issues in eWOM research, the most cited papers published during 2014–2019 were carefully analyzed. According to Camberia (2016), future researchers should use the ensembled application of semantic knowledge and machine learning for deeper consumer insights. Next-generation sentiment mining systems should use psychologically motivated and brain-inspired reasoning methods (Camberia, 2016). Besides sentiment analysis, hybrid machine learning techniques should be used to classify sentiments (Tripathy et al., 2016). Future optimization models should use well-established theories in industrial design, marketing, and advertising (Zhang et al., 2016) and linguistic patterns for deep learning to detect sarcasm because irony may reverse sentence polarity (Poria et al., 2015). According to Giatsoglou et al. (2017), future researchers should work on high inflection languages and consider emotional lexicons for big data sentiment analysis like Twitter datasets.

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