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The State of Artificial Intelligence in Marketing With Directions for Future Research

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ABSTRACT

Today, artificial intelligence (AI) is becoming increasingly important in both industry and academics. To investigate AI in marketing, the authors have used bibliometric study, social network analysis (SNA), main path analysis, and content analysis to examine the top 10 authors, top 20 most cited articles, and top 11 milestone papers from the 628 article sample. Bibliometric study identified leading authors, documents, universities, countries, and sources of these articles. By using SNA, they spotted an academic social network of crucial publications. Moreover, they recognized 11 milestone articles that constitute the main knowledge flow in AI marketing through main path analysis. Finally, they discussed future directions based on the findings. The study is one among a few studies that have used bibliometric analysis methods to analyze and visualize the citation network of the AI-marketing interface.

KEYWORDS

Artificial Intelligence, Bibliometric Analysis, Literature Review, Main Path Analysis, Marketing Research, Social Network Analysis

1. INTRODUCTION

Marketing is a complex decision-making discipline that involves not only the commonly known 4Ps (product, price, promotion, and place) but also strategic issues such as new product development (NPD), customer relationship management (CRM), selling strategies, market segmentation, positioning and targeting, international marketing, marketing research, etc. (Rutz & Watson, 2019). With the ever-increasing amount and importance of "big data," now scholars are interested in whether appropriate decision-making technologies can solve marketing problems.

Artificial intelligence (AI), which refers to machines and software that exhibit human intelligence, can provide great opportunities to facilitate decision-making in marketing. The existence of AI could be traced back to 1955 when John McCarthy coined the term Artificial Intelligence. In his work, AI was defined as "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al., 1955). Since then, AI definition has evolved as "manifested by machines

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that exhibit aspects of human intelligence" (Huang & Rust 2018, p. 155). With the tools of machine learning, deep learning, neural networks, and natural language processing, AI could "interpret external data correctly, learn from such data, and exhibit flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). There are substantial AI-based examples (Kumar et al., 2016, Huang & Rust, 2017). For instance, when you post a photo on Facebook, it can automatically recognize you and your friends' faces and tag their names; when you are off, Amazon's Alexa and Google-Home work as virtual assistants to take care of your home, set the room temperature, manage your schedules, and control the lights; when you ask Amazon for return, its chatbot serves you all the time.

In this regard, the definition of AI in marketing could be illustrated by those business recognitions. AI can implement simple marketing transactions, such as translating emails or phone calls to automate replies, reading customers' online comments, and smart retailing by recommending products to customers. AI can leverage machine learning tools to analyze large volumes of customer digital footprints, including reviews, video, images, subscriptions, browsing history, webpage activities, and even facial expression data. Those analyses empowered AI to gain a deep understanding of customers' preferences, behaviors, likes/dislikes, trends, etc. AI could engage customers through real-time interaction and customized digital advertising recommendations. This fast movement allows AI to stay actively engaged with customers to influence their decision-making.

Due to the ever-increasing interest and importance of AI applications in our marketing field, a comprehensive review that precisely analyzes the AI-marketing (AIM) interface literature is imperative to properly understand the constantly growing AIM field (Siau & Yang, 2017). The literature review aims to provide a holistic view and meaningful research questions in AIM studies. Bibliometric study, social network analysis, main path analysis, and content analysis are effective tools used to conduct this systematic literature review.

Bibliometric studies explore a large amount of content in academic journals, including the journal citation information, to identify its leading trend (Bonilla et al., 2015). Journal authors, keywords, affiliations, and citations are also collected and traced in a bibliometric study. Social network analysis is usually followed after a bibliometric study to provide insights about institutions, countries, and keyword collaboration networks. Social network analysis monitors and interprets social ties among social nodes to visualize how the relationships in a group relate to each other and determine the types of relationships that lead to effective outcomes (Stangor, 2015). The main path analysis is based on social network analysis to detect the meaningful and traceable main paths representing the journals in the social network. The importance of path is measured by "counting the number of times a citation link has been traversed if one exhausts the search from a set of starting nodes to another set of ending nodes" (Hummon & Coreian 1989, p. 50).

The remainder of this paper is organized into the following sections. It starts with section 1 introducing its background and states the contributions we are trying to make: to provide a holistic view and meaningful research questions in AIM studies. Following the introduction, we have conducted a literature review (section 2) about marketing bibliometric studies and artificial intelligence in marketing; we found that there have been a limited number of publications examining AI in marketing. Thus, a systematic bibliometric review of AIM is needed, while a comparative and quantitative analysis of AIM studies will provide more insight for scholars. Section 3 described how we obtained the literature and implemented four methods: bibliometric study, social network analysis, main path analysis, and content analysis to analyze those articles. Section 4 presented the results followed by major findings within the study and pointed out potential future research streams in section 5.

2. LITERATURE REVIEW

2.1 Literature Review of Marketing Bibliometric Studies

Bibliometric analysis has been widely used in literature reviews on a broad range of topics in the business discipline: including marketing, advertising (Kim & McMillan, 2008), sales management (Johnson, 2006), accounting (Zhong et al., 2016), strategic management (Vogel & Guttel, 2013), and supply chain management (Asgari et al., 2016), and so on.

2.2 Literature Review of Artificial Intelligence in Marketing

Recently, as an application of digital marketing tools, artificial intelligence (AI) has been actively catching people's attention. Generally, AI is relevant to any intellectual task. There are many applications in the business world (Balducci & Marinova, 2018, Thomaz et al., 2020). Banks use artificial intelligence systems to organize operations, maintain investments in stocks, detect fraud, and manage properties (Fethi & Pasiouras, 2010). AI tools make individualized pricing easy to achieve through estimating individualized demand and supply curves (Marwala & Hurwitz, 2017). Using AI tools, marketers can now track customers' digital footprints to predict their general online behaviors and target them with personalized promotions and products (Hennig-Thurau et al., 2015, Matz et al., 2017). Recently, the applications of personality computing AI tools have been used to reduce the cost of advertising campaigns because it adds psychological targeting to traditional behavioral targeting (Celli et al., 2017). AI is still a relatively new research stream, and there is a limited number of publications presenting artificial intelligence applications in marketing. Yang and Siau (2018) published a longitudinal case study exploring whether AI and robots will replace salespeople and marketers. Marinchak et al. (2018) explored new rules of engagement with the advent of AI. They recommended marketers to integrate virtual personal assistants to meet users' actual needs. Mitić (2019) concluded that with the new artificial neural network algorithms, AI applications in marketing would become more personalized to reflect customer needs better. IT companies that run in chatbots, robots, and other AI applications will have tremendous advantages in marketing. André et al. (2018) articulated that although artificial intelligence-based tools can provide customers convenience and efficiency, it also undermines consumers' sense of autonomy. Their papers explored the boundaries within which new technologies may enhance or diminish consumers' perception of control. Kose and Sert (2017) examined how artificial intelligence tools could integrate digital content to upgrade content marketing. Their paper proposed a model to apply AI-based optimization algorithms to content marketing scenarios to maximize success ratios. Jarek and Mazurek (2019) found that AI is widely used in the marketing field, although most use is operational. The uncertainty of the outcomes of AI impedes the diffusion and adoption of AI in the business field. Doğan (2018) developed an AI mobile banking acceptance model. AI was studied in many marketing domains, such as AI in retailing (Grewal et al., 2017), AI in banking (Leone et al., 2021), AI in automotive (Davenport et al., 2020, Vlačić et al., 2021), AI in fashion (Davenport et al., 2020), AI in sales and service (Leminen et al., 2018; Mustak et al., 2021), Cloud service in AI (Živković 2019), AI in manufacturing (Li et al., 2017; Mele et al., 2018), AI ethical issues (Stahl et al., 2021), and AI enhances market performance (Paschen, Pitt, & Kietzmann 2020). Future research in AI could explore more on the use of AI technology and applications, the role of institutional support, and the importance of data protection and ethics in AI. More details are shown in table 1.

These works of literature provide a good view of the current state of AIM research. Although AI has been a hot topic for a while, AI academic studies are still in an infancy stage. Until now, there have been a limited number of publications examining AI in marketing. Thus, a systematic bibliometric review of AIM is needed; a comparative and quantitative analysis of AIM studies will provide more insight for scholars.

Table 1. AI research in marketing domains

Domains	FINDINGS OF ITS FUNCTIONS	EXAMPLES	STUDIES
AI IN RETAILING	● analyze and process customer information, ● inform product recommendations, ● provide product physical locations within a store ● response to simple customer requests	e.g., Virchbox AI can predict what customer wants	Grewal, Roggeveen, & Nordfält (2017)
AI IN BANKING	● prevent fraud ● detect unauthorized use of credit cards ● customized offers	e.g., Knightscope's k5 is a security robot with superior sensing capabilities to patrol in malls and bank office	Leone et al., (2021)
AI IN AUTOMOTIVE	● observe and analyze speed and direction of the other cars ● process traffic light and other cars information to carry out actions ● driverless cars	e.g., Tesla will impact auto insurance, taxi service, and whether customer behaviors in car purchase.	Davenport et al., (2020), Vlačić et al., (2021)
AI IN FASHION	● creative fashion design and product ideas	e.g., Stitch fix AI creates a set of stylish clothing items for customers.	Davenport et al., (2020)
AI IN SALES AND SERVICE	● automate part of the sales process ● chatbot answers customer questions ● analyze customer satisfactions to provide novel services	e.g., Conversica AI bots interact with customer service and sales inquiries.	Leminen et al., (2018); Mustak et al., (2021)
CLOUD SERVICE IN AI	● cloud service provide technological platforms to support ai. ● it provides technological lens to analyze data and facilitates ai self-learning.	e.g., Amazon web services (AWS) enhances amazon personalize; azure in microsoft cloud service is powerful in supporting machine and deep learning.	Živković (2019)
AI IN MANUFACTURING	● intelligent design and creative ideas ● intelligent robot ● intelligent product life cycle manufacturing technology and platform	e.g., IBM interactive AI provides inputs to facilitate business process.	Li et al., (2017) ; Mele, Spena, & Peschiera, (2018)
AI ETHICAL ISSUES	● problems of algorithmic biases ● manipulation of the large data set required by ai techniques. ● customer worry data privacy	e.g., Amazon abandoned one AI tool that rate job applicants, because it discriminates female applicants.	Stahl et al., (2021)
AI ENHANCE MARKET PERFORMANCE	● better sales performance ● high customer satisfaction and loyalty ● better customer prediction	e.g., Hyatt hotels group used AI increase room revenue up to 60%.	Paschen, Pitt, & Kietzmann, (2020)

3. MATERIALS AND METHODS

The study aims to identify and analyze AI in marketing studies to classify emerging themes and point out future research directions. The unit of measure used in this study was individual articles published with the broad topics of artificial intelligence stream and marketing stream interface. We collect our sample articles by conducting a thorough search using a series of keywords across Web of Science (WOS) database.

Keywords represent the essence of articles, and their choice is critical. To capture as many articles as possible, we have used the following search strings to present AI stream: ("artificial intelligence," or "machine learning," or robot), we also used strings: ("marketing," or "new product" or "customer relationship," or "selling," or "market planning," or sale, or "marketing planning," or brand, or "selling capability," or "new product development capability," or "customer relationship management capability," or "marketing planning capability") to capture more marketing activities. The final sample article was generated from (AI streams) AND (marketing streams). The quotation marks mean the exact phrase is searched; the keywords without quotation marks mean the phrases that contain those keywords are searched.

We filtered out articles published before 1982 and non-English because we noticed that AI in marketing had very few publications before 1982. The study only included published articles indexed by the Web of Science (WOS) database. Book reviews, comments to the editor, and similar articles were excluded from the analysis. We also manually excluded the duplicate articles and the articles that are not in a business setting. After ruling out all the duplicates, it generated 628 articles from the years 1982 to 2019. Although this dataset did not cover every AIM article ever published, the rigorous data selection process ensures that the dataset reasonably represents the AI field. We configured all 628 papers into the WOS citation format and fed the data into R software to do the bibliometric analysis. The software systems that are utilized for network analysis and main path analysis are VOSviewer 1.6.5(Appio et al., 2017) and Pajek 5.0.1 (Strozzi et al., 2017). The following flow chart in figure 1 describes the methods in our studies.

4. RESULTS

We analyzed the literature review on AIM using a bibliometric study, social network analysis, main path analysis, and content analysis.

4.1 Bibliometric Result: Basic Statistics

The 628 articles generated 7951 cited references, which corresponded to an average of 12.66 citations per document. Statistics in table 2 shows that teams of researchers have widely explored artificial intelligence, machine learning, robot, and marketing. The average research team consisted of 3.36 authors per document.

The AI-marketing interface does provide good basic statistical information for us to understand the AIM field. The further step is to explore the link between AIM and performance. Theoretically, AI could be interpreted as a capability that is added to a firm's functional activities. The bibliometric study also showed that the *Strategic Management Journal* is the top journal and a good resource for finding those references.

Figure 2 shows the annual scientific production of the articles that discussed those topics. In the years from 1982 to 2012, the number of annual productions was below or around twenty-five. Before 1980s, AI research mainly focused on math and logical reasoning problems; because of the considerable technical challenges, we did not see a surge in AI research (Wirth, 2018). The studies on AI in marketing were underdeveloped. The past decade has witnessed impressive breakthroughs in AI. Interactions between firms and customers are increasingly more customized, generating considerable amounts of digitalized footprints. Thanks to greater computing power and the availability of big data

Figure 1. Methods

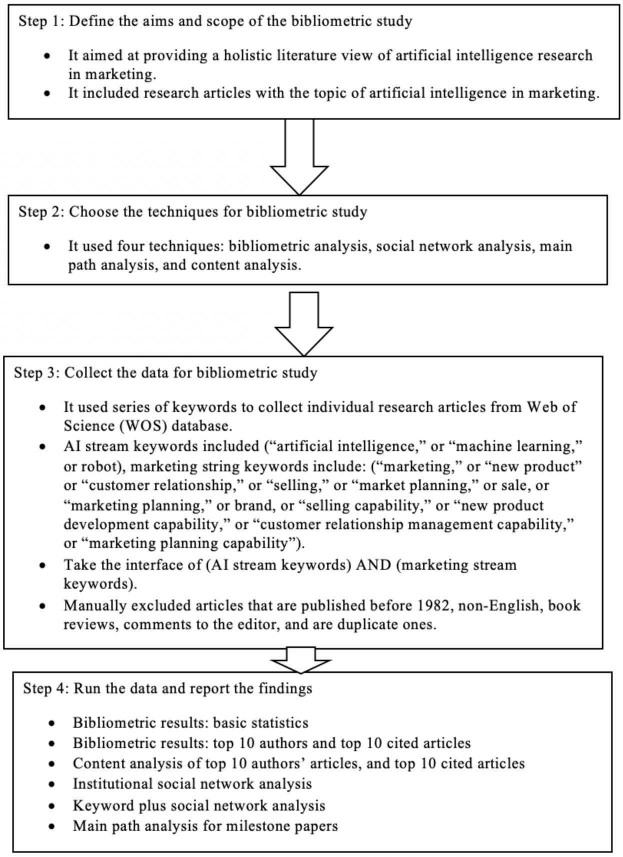


Table 2. Descriptive statistic information

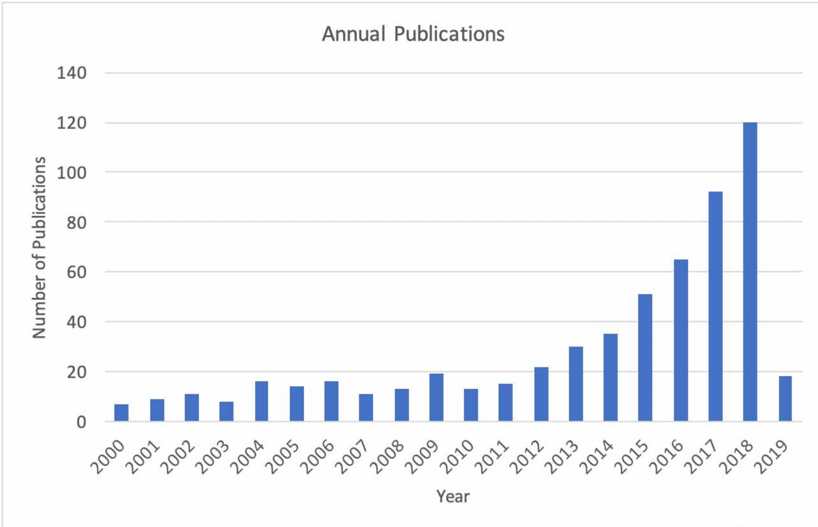
	AI-marketing interface
TOTAL NUMBER OF ARTICLES	628
PERIOD	1982-2019
AVERAGE CITATIONS PER DOCUMENT	12.66
CO-AUTHORS PER DOCUMENT	3.36

and more sophisticated algorithms, AI research in marketing is booming. Six years later (in 2018), the number of annual publications surged to 125, almost five times the sum of the publications from the past 30 years, suggesting that interest in the topic will continue to grow.

4.2 Bibliometric Results: Leading Authors and Documents

The top 10 leading authors by the number of documents published are listed in Table 3. Table 3 also shows the other metrics (such as h-index, g-index, m-index, and total citations) for comparison with the number of publications. Although different metrics show different ranks of the top authors, generally, they provide us with good references about the author's importance in the field. The first

Figure 2. Annual scientific production of articles on specified topics



top author is Marko Bohanec, the professor of Engineering and Management at the University of Nova Gorica (Slovenia). The second top author is Mirjana Kljajic Borstnar, a professor of Information Systems at the University of Maribor (Slovenia). After Bohanec and Borstnar, Casillas is a professor of Computer Science and Artificial Intelligence at the University of Granada (Spain), Yoosin Kim is a professor of Management Information Systems at Chungbuk National University (South Korea), and Marko Robnik-Šikonja is a Professor of Computer Science and Informatics at University of

Table 3. Leading publishing authors

Author	*H*	*G*	*M*	*TC*	*TP*	*% of 628*	*Department*	*University*	*Country*
Marko Bohanec	2	3	0.67	14	5	0.79	Eng & Mgmt	Uni of Nova Gorica	Slovenia
Mirjana Kljajic Borstnar	2	3	0.67	14	5	0.79	IS	Uni of Maribor	Slovenia
Jorge Casillas	5	5	0.45	134	5	0.79	CS & AI	Uni of Granada	Spain
Yong-Seog Kim	3	4	0.6	21	5	0.79	Mgmt & IS	Chungbuk National Uni	South Korea
Marko Robnik-Šikonja	2	3	0.67	14	5	0.79	CS & Informatics	Uni of Ljubljana	Slovenia
Eric Cambria	3	4	0.5	214	4	0.63	CS & Eng	Nanyang Technological Uni	Singapore
Sooyoung Cho	3	4	0.21	66	4	0.63	JRNL & Comm	KyungHee Uni	South Korea
Francisco J. Martínez-López	4	4	0.36	62	4	0.63	Mktg	Uni of Granada	Spain
Dirk Van den Poel	4	4	0.25	235	4	0.63	Mktg	Ghent Uni	Belgium

Note: (1) H-index is based on the set of the scientist's most cited papers and the number of citations that they have received in other publications. (2) G-index is calculated based on the distribution of citations received by a given researcher's publications. (3) M-index is the H-index divided by the number of years that a scientist has been active. (4) TC is the total citations. (5) TP is the number of publications.

Ljubljana (Slovenia). By no surprise, the top 5 scholars in AIM studies are dominated by engineering and computer science scholars.

Table 4 shows the leading author's documents. Due to the length limit, we chose the top 10 articles from these top authors. Please note that the top authors (Marko Bohanec and Mirjana Kljajic Borstnar) collaborate extensively, and their top documents are the same. Therefore, we merge them together.

We have conducted content analysis to explore the main themes in top authors' research. Content analysis uses qualitative and quantitative research techniques to explore and analyze data obtained from written documents. The main goal of content analysis is to enhance researchers' capabilities in identifying new phenomena from exploiting documents. The results often include concepts or categories of topics that summarize the original information investigated. Guided by Elo and Kyngäs (2008), we have used three phases: preparing, organizing, and reporting to conduct our content analysis. In the preparing phase, we aim to identify the common characteristics that can be categorized to describe the information investigated. We manually go through each article to identify the keywords, topic, context, research methods, and findings to classify its themes in the organizing phase. Finally, in the reporting phase, we follow Miah et al. (2017) to present our structured findings.

Our content analysis of the top 10 authors finds that those articles are examining artificial intelligence, machine learning, or robot in marketing topics: such as sales, WOM (word of mouth), Twitter, service, distribution channel, online knowledge sharing service, and consumer behavior modeling. After systematically reviewing their content, keywords, context, methods, and findings, we classified them into three main themes: B2B sales forecasting, machine learning techniques acceptance model, and machine learning knowledge generation and diffusion within the organizational setting.

Theme 1: B2B Sales Forecasting

The process of B2B sales forecasting is a complex decision-making process. In the big data era, the high data collection cost, data computation load, and complicated dataset dimensionalities make effective sales forecasting challenging. To have an effective sales forecast, firms need to identify the correct rank of data features with high impacts (Bohanec et al., 2017). In reality, customers and users keep adding new features to the existing classification models, making it harder to interpret the new features. Bohanec et al. (2017) developed an organizational model that uses a machine learning model and a general explanation method to evaluate the new customer features. Later in 2018, Bohanec et al. (2018) introduced a guideline to determine the sample size needed to estimate the impact of a new feature on sales forecasting. Their results demonstrate that machine learning models have significant advantages in evaluating sellers' actions and outlining the general recommendations in sales strategy (Bohanec et al., 2017).

B2B sales forecasting provides substantial evidence that AI and machine learning techniques could augment a firm's selling capabilities and its subsequent sales performance. Although Bohanec, Borštnar, and Robnik-Šikonja's manuscripts are from a computer science and engineering perspective, the key technical problems they identified and the key machine learning tools and models they built provide significant managerial implications to sales managers and practitioners. This stream of study also enlightens the further exploration of the theory-driven mechanisms behind the curtain. Professional selling involves several steps from a marketing perspective: prospecting, approaching, presenting, overcoming objection, and following up. Researchers can study how AI-based systems or tools are utilized in these steps. Revealing these mechanisms will help managers understand how AI could augment their sales activities and how to configure their organizational resources to strategically optimize this bonus.

Theme 2: Machine Learning Acceptance Model

Bohanec et al. (2017) also addressed the problem of the low acceptance rate of machine learning models in the business field. The participatory approach of action design research (ADR) was proposed to increase user acceptance of the machine learning model. The proposed framework was

Table 4. Leading publishing authors' documents and keywords

Articles	*Keywords*	*Classification*	*Context*	*Methods*	*Findings*
Bohanec, M., Kljajić Borštnar, M., & Robnik-Šikonja, M. (2018). Number of Instances for Reliable Feature Ranking in a Given Problem. Business systems research journal: international journal of the Society for Advancing Business & Information Technology (BIT), 9(2), 35-44.	machine learning; feature ranking; feature evaluation	B2B sales forecasting	B2B sales	Feature evaluation measure relief and the bootstrap-based estimation of confidence intervals for feature ranks.	A combination of the feature evaluation measure Relief and the bootstrap-based estimation of confidence intervals can be used to reliably estimate the impact of a new feature in a B2B sales problem.
Bohanec, M., Robnik-Šikonja, M., & Borštnar, M. K. (2017). Organizational learning supported by machine learning models coupled with general explanation methods: A Case of B2B sales forecasting. Organizacija, 50(3), 217-233.	decision support; organizational learning; machine learning; explanations; B2B sales forecasting	B2B sales forecasting; Machine learning acceptance model	B2B sales	Participatory approach of action design research was used to promote acceptance of the model among users. ML model was built following CRISP-DM methodology and utilizes R software environment.	Based on the explanations of the ML model predictions, the users' forecasts improved. Furthermore, when the users embrace the proposed ML model and its explanations, they change their initial beliefs, make more accurate B2B sales predictions and detect other features of the process, not included in the ML model.
Bohanec, M., Borštnar, M. K., & Robnik-Šikonja, M. (2017). Explaining machine learning models in sales predictions. Expert Systems with Applications, 71, 416-428.	Machine learning; Prediction explanation; Intelligent system; Black-box models; B2B Sales forecasting	B2B sales forecasting	B2B sales	Uniform explanations are generated on the level of model/individual instance and support what-if analysis.	The presented method is able to evaluate sellers' actions and to outline general recommendations in sales strategy
Bohanec, M., Kljajić Borštnar, M., & Robnik-Šikonja, M. (2017). Estimation of minimum sample size for identification of the most important features: a case study providing a qualitative B2B sales data set. Croatian Operational Research Review, 8(2), 515-524.	data set reduction; B2B sales forecasting; machine learning; sample size	B2B sales forecasting	B2B sales	Machine learning techniques	A relatively small instance subset is sufficient for identifying the most important features when rank is not important.
Bohanec, M., Robnik-Šikonja, M., & Kljajić Borštnar, M. (2017). Decision-making framework with double-loop learning through interpretable black-box machine learning models. Industrial Management & Data Systems, 117(7), 1389-1406.	Machine learning, Double-loop learning, B2B sales forecasting, Explanation of black-box models	B2B sales forecasting; Machine learning acceptance model	B2B sales	Participatory approach of action design research (ADR)	The provided ML model explanations efficiently support business decision-makers, reduce forecasting error for new sales opportunities, and facilitate discussion about the context of opportunities in the sales team.

continued on next page

Table 4. Continued

Articles	*Keywords*	*Classification*	*Context*	*Methods*	*Findings*
Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. Industrial Marketing Management, 42(4), 489-495.	Intelligent systems; Marketing intelligent systems; Industrial marketing; Literature review; Insights	Knowledge generation and diffusion	Industrial marketing	Literature review	They carry out a historical literature review of artificial intelligence-based systems applied to marketing, covering a time period of several decades (from the 1970s to the present day) with a special focus on applications to industrial marketing.
Orriols-Puig, A., Martínez-López, F. J., Casillas, J., & Lee, N. (2013). Unsupervised KDD to creatively support managers' decision making with fuzzy association rules: A distribution channel application. Industrial Marketing Management, 42(4), 532-543.	Intelligent systems; KDD; Unsupervised learning; Management support; Genetic fuzzy systems	Knowledge generation and diffusion	Distribution channel	A novel intelligent system that incorporates fuzzy logic and genetic algorithms to operate in an unsupervised manner.	The method has significant potential to improve the analysis of marketing and business databases in practice, especially in non-programmed decisional scenarios, as well as to assist scholarly researchers in their exploratory analysis.
Martínez-López, F. J., & Casillas, J. (2009). Marketing Intelligent Systems for consumer behaviour modelling by a descriptive induction approach based on Genetic Fuzzy Systems. Industrial Marketing Management, 38(7), 714-731.	Marketing modelling; Management support; Analytical method; Knowledge discovery; Genetic Fuzzy Systems; Methodology	Knowledge generation and diffusion	Consumer behavior setting	Genetic Fuzzy Systems, a specific hybridization of artificial intelligence methods.	The valuation of its performance and utility is very positive in consumer behavior modelling.
Sánchez, L., Couso, I., & Casillas, J. (2009). Genetic learning of fuzzy rules based on low quality data. Fuzzy Sets and Systems, 160(17), 2524-2552.	Genetic fuzzy systems; Fuzzy rule-based systems; Vague data	Knowledge generation and diffusion	Marketing	Genetic fuzzy systems (GFS)	The techniques proposed here are shown to improve the generalization properties of another knowledge base obtained from crisp training data.
Casillas, J., & Martínez-López, F. J. (2009). Mining uncertain data with multi-objective genetic fuzzy systems to be applied in consumer behavior modelling. Expert Systems with Applications, 36(2), 1645-1659.	Consumer behavior; Fuzzy logic; Genetic algorithms; Knowledge extraction; Machine learning; Marketing	Knowledge generation and diffusion	Consumer behavior setting	A complete methodology that considers the different stages of knowledge discovery: data collection, data mining, and knowledge interpretation dynamically.	It is more effective in modeling consumer behaviors.

demonstrated with a data mining methodology in a B2B sales forecasting context. The new machine learning techniques helped business decision-makers reduce forecasting errors and to find new sales opportunities.

The machine learning acceptance model is a good starting point to facilitate AI acceptance model development. An early survey shows that most marketing managers say that they can foresee the benefits of AI; however, only 10% of the surveyed managers are currently using them. Although AI is promising, it is still at the infancy stage, and it is reasonable to predict that marketers are not confident using AI. From an engineering perspective, Bohanec et al. (2017) studied the factors that impact machine learning acceptance. The results are appealing and exciting. They encourage us to think outside of the box to explore other organizational factors that impact AI acceptance. The technology-organization-environment (TOE) framework (Tornatzky & Fleischer, 1990), institutional theory (Scott, 1987), and the resource-based view of the firm (Wernerfelt, 1984) have accumulated a rich stream of studies examining disruptive technology acceptance. They provide sound theoretical foundations to employ the AI acceptance model.

Theme 3: Machine Learning Knowledge Generation and Diffusion

Currently, market-oriented firms find it challenging to leverage the right data to make correct decisions. New technological methods (e.g., machine learning techniques and AI) enhance a firm's ability to exploit data and to generate appropriate knowledge (Orriols-Puig et al., 2013; Martínez-López & Casillas, 2009; Sánchez et al., 2009; Casillas & Martínez-López, 2009). Theoretically, knowledge is the mechanism that links AI tools and firm performance, but how the new technologies are used to generate this knowledge and what kind of marketing activities can implement it remains unknown. Martínez-López and Casillas (2013) systematically reviewed how AI-based systems are used to segment business markets, manage customer relationships, facilitate organizational buying processes, manage business intelligence and knowledge, manage personal selling, and improve service management in the business market. This framework provides a good theoretical reference for understanding how AI-based systems and machine learning techniques could be used in various marketing activities and strategies. From a marketing perspective, knowledge is generated and diffused through marketing activities. Innovation diffusion theory, resource-based views, and technology acceptance models are rooted in knowledge. Knowledge is the resource that facilitates all procedures and steps. Knowledge generation and diffusion perspectives align with the dynamic capability theory (Teece et al. 1997). The combination of both theories helps to articulate the theoretical mechanisms that connect AI-based tools and marketing performance.

4.3 Bibliometric Results: Most Cited Papers

The top twenty most cited papers are shown in Table 5. We also used three phases: preparing, organizing, and reporting to conduct a content analysis for tope twenty cited papers (Elo & Kyngäs, 2008). After identifying the common characteristics that can be categorized to describe the information investigated, we manually go through each article to recognize the keywords, topic, context, research methods, and findings to generate its themes. Finally, we follow Miah et al. (2017) to present our structured findings. As the table shows, thirteen out of the twenty papers are from marketing-related journals or topics. These most cited papers guide us toward the most researchable areas in AIM. Specifically, the most cited papers mentioned could be categorized into five themes: effective selling, customer relationship management (CRM), new product development (NPD), advertising and promotion, and pricing.

Theme 1: Effective Selling:

Effective selling, especially sales forecasting and prediction, plays significant roles in AIM studies (as shown in leading authors' documents, e.g., Cui & Curry, 2005; Evgeniou et al., 2007). One impressive

Table 5. Most Cited papers

Document	*Keywords*	*Classification*	*Context*	*LC*	*Methods*	*Findings*
Cui, D., & Curry, D. (2005). Prediction in marketing using the support vector machine. Marketing Science, 24(4), 595-615.	automated modeling; choice models; kernel transformations; multinomial logit model; predictive models; support vector machine	Effective selling; pricing	Pure mathematical modelling	8	Support vector machine	It identifies and empirically proves that the support vector machine has a better prediction than other traditional methods in marketing.
Rui, H., Liu, Y., & Whinston, A. (2013). Whose and what chatter matters? The effect of tweets on movie sales. Decision Support Systems, 55(4), 863-870.	Twitter; Social broadcasting networks; Social media; Word-of-mouth; Movie sales; Dynamic panel data	CRM	Tweets on movies	7	Machine learning algorithm	Twitter WOM has a significant effect on product sales.
Cheung, K. W., Kwok, J. T., Law, M. H., & Tsui, K. C. (2003). Mining customer product ratings for personalized marketing. Decision Support Systems, 35(2), 231-243.	Recommender systems; Personalized marketing; Support vector machine; Latent class model	Effective selling; CRM; advertising and promotion	Movie recommendations	6	Recommender systems; Support vector machine; Latent class model	It studied support vector machine and the latent class model in mining customer product ratings for personalized marketing.
Myslín, M., Zhu, S. H., Chapman, W., & Conway, M. (2013). Using Twitter to examine smoking behavior and perceptions of emerging tobacco products. Journal of medical Internet research, 15(8).	Social media, twitter messaging, smoking, natural language processing	NPD; CRM	Tweets about smoking behavior	6	Content and sentiment analysis	Sentiment analysis and machine learning classifiers are used to analyze tobacco-related tweets.
Ghose, A., Ipeirotis, P. G., & Li, B. (2012). Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. Marketing Science, 31(3), 493-520.	User-generated content; social media; search engines; hotels; ranking system; structural models; text mining; crowdsourcing	NPD; CRM; pricing	Hotel reservations	5	Text mining, image classification, social geotagging, human annotations, and geomapping	Social media techniques can be incorporated into a demand estimation model to obtain an effective product search ranking system.
Chang, P. C., Wang, Y. W., & Tsai, C. Y. (2005). Evolving neural network for printed circuit board sales forecasting. Expert Systems with Applications, 29(1), 83-92.	Sales forecasting; Printed circuit board; Genetic algorithm; Neural network	Effective selling	Printed circuit board industry	4	Evolving Neural Networks (ENN) forecasting model	Evolving neural networks is used for effective sales forecasting.
Cui, G., Wong, M. L., & Lui, H. K. (2006). Machine learning for direct marketing response models: Bayesian networks with evolutionary programming. Management Science, 52(4), 597-612.	Direct marketing; Bayesian networks; evolutionary programming; machine learning; data mining	CRM; pricing	Direct marketing	4	Bayesian networks	This study finds Bayesian networks have significant advantages and accuracy in predicting direct marketing results.
Evgeniou, T., Pontil, M., & Toubia, O. (2007). A convex optimization approach to modeling consumer heterogeneity in conjoint estimation. Marketing Science, 26(6), 805-818.	Bayesian analysis; data mining; econometric models; estimation and other statistical techniques; hierarchical Bayes analysis; marketing research; regression and other statistical techniques	Effective selling; CRM	Pure mathematical modelling	4	convex optimization and statistical machine learning	This study finds that statistical machine learning provides a new alternative in modeling consumer heterogeneity in conjoint estimation.
Abernethy, J., Evgeniou, T., Toubia, O., & Vert, J. P. (2008). Eliciting consumer preferences using robust adaptive choice questionnaires. IEEE Transactions on Knowledge and Data Engineering, 20(2), 145-155.	Marketing, machine learning, statistical, interactive systems, personalization, knowledge acquisition.	NPD	New product development marketing context	4	Regularization Networks and adaptive questionnaire	This study finds that machine learning has great potential in marketing personalization and knowledge acquisition.

continued on next page

Table 5. Continued

Document	*Keywords*	*Classification*	*Context*	*LC*	*Methods*	*Findings*
Casillas, J., & Martínez-López, F. J. (2009). Mining uncertain data with multiobjective genetic fuzzy systems to be applied in consumer behavior modeling. Expert Systems with Applications, 36(2), 1645-1659.	Consumer behavior; Fuzzy logic; Genetic algorithms; Knowledge extraction; Machine learning; Marketing	Effective selling; NPD	Consumer behavior setting	3	Machine learning techniques	This study targets machine learning techniques in data collection, data mining, and knowledge interpretation in the marketing field.
Bhattacharyya, S. (1999). Direct marketing performance modeling using genetic algorithms. INFORMS Journal on Computing, 11(3), 248-257.	Genetic algorithms, data mining, database marketing, profile modeling, resampling	Effective selling; pricing	Pure mathematical modelling	2	Genetic algorithm based machine learning techniques	A new machine learning algorithm is found to be effective in predicting direct marketing performance.
Balakrishnan, P. V., Gupta, R., & Jacob, V. S. (2004). Development of hybrid genetic algorithms for product line designs. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 34(1), 468-483.	Artificial intelligence, attribute importance, beam search, GA, hybrid genetic algorithms, marketing, meta-heuristic techniques.	NPD	Pure mathematical modelling	2	Artificial intelligence (AI) based meta-heuristic techniques namely genetic algorithms	This study finds AI is effective in designing product lines.
Shin, H., & Cho, S. (2006). Response modeling with support vector machines. Expert Systems with Applications, 30(4), 746-760.	Response modeling; Direct marketing; Support vector machines (SVMs); Pattern selection; Class imbalance; Scoring	Pricing	Pure mathematical modelling	2	Support Vector Machine (SVM)	This study designs effective response modeling with support vector machines.
Martínez-López, F. J., & Casillas, J. (2009). Marketing Intelligent Systems for consumer behavior modeling by a descriptive induction approach based on Genetic Fuzzy Systems. Industrial Marketing Management, 38(7), 714-731.	Marketing modelling; Management support; Analytical method; Knowledge discovery; Genetic Fuzzy Systems; Methodology	CRM	Consumer behavior setting	2	Genetic Fuzzy Systems, a specific hybridization of artificial intelligence methods.	A new machine learning technique is used in marketing intelligent system to model consumer behavior.
Ikeda, K., Hattori, G., Ono, C., Asoh, H., & Higashino, T. (2013). Twitter user profiling based on text and community mining for market analysis. Knowledge-Based Systems, 51, 35-47.	Web mining; Market analysis; User profiling; Twitter; Text analysis; Community analysis; Machine learning	CRM	Tweets	2	A hybrid text-based and community-based method	Data mining techniques are used to reveal twitter user profiles.
Kwok, L., & Yu, B. (2013). Spreading social media messages on Facebook: An analysis of restaurant business-to-consumer communications. Cornell Hospitality Quarterly, 54(1), 84-94.	social media, Facebook, marketing, communication, restaurant, text classification	Effective selling: CRM	Facebook	2	Text classification	Text classification technique is used to analyze restaurant business to consumer communications on Facebook.
Poria, S., Gelbukh, A., Cambria, E., Hussain, A., & Huang, G. B. (2014). EmoSenticSpace: A novel framework for affective common-sense reasoning. Knowledge-Based Systems, 69, 108-123.	Sentic computing; Opinion mining; Sentiment analysis; Emotion recognition; Personality detection; Fuzzy clustering	CRM	EmoSenticSpace	2	Natural language processing; sentiment analysis	Emotion recognition and sentiment analysis are used for effective common-sense reasoning.

Note: (1) LC means location citation, how many times the paper is being cited within the 628 articles.

article is from Chang et al. (2005). Their work applied a neural network technique to compare the before and after sales forecasts. The results demonstrate that AI tools are effective in predicting sales.

Theme 2: Customer Relationship Management

In marketing studies, emotions play a crucial role in linguistic understanding and common sense reasoning. Prior machine-learning tools find it difficult to interpret emoticons accurately. A new framework, EmoSentic Space, was proposed by Poria et al. (2014) to provide emotional labels and scores for a large set of natural language concepts. EmoSenticSpace can reach a 92.15% accuracy rate in a comparison of standard facial expressions and body language. In a social broadcasting network (e.g., Facebook, Twitter, and Instagram), customer word of mouth can be monitored and analyzed for customer relationship management. Many researchers suggest that managers who want to leverage SBN (social broadcasting network) should implement machine learning tools to identify and monitor people's attitudes towards influential topics (Rui et al., 2013; Kwok & Yu, 2013; Ikeda et al., 2013). SBN and machine learning techniques are effective combinations to upgrade customer relationship qualities. Machine learning techniques can be used to improve customer relationship management by identifying customer emotions and tailoring corresponding strategies.

Theme 3: New Product Development

A central problem in new product development is to understand customer preferences. Traditionally, marketers use a pre-determined questionnaire to ask respondent preferences about new product designs. But with the development of machine learning techniques, the adaptive questionnaire has gained increasing interest among researchers and practitioners (Abernethy et al., 2008). The questions can be redesigned based on the respondent's previous response. This tailored questionnaire has led to a significant increase in the new product development success rate (Abernethy et al., 2008). AI-based tools can also upgrade product line design. Balakrishnan et al. (2004) empirically demonstrated the efficacy of AI-based techniques (such as genetic algorithms) in solving product line design problems. New product development (NPD) is a complex decision-making process. Idea generation requires a significant amount of creativity. The newly developed machine learning techniques change the traditional paradigm in new product development. These results and applications also encourage the further exploration of more AI-based tools in NPD.

Theme 4: Advertising and Promotion

Advertising and promotion represent another important research stream in marketing literature that machine learning techniques have upgraded. Kwok and Yu (2013) found that spreading social media messages on Facebook was an effective promotional method. Social media is one representative online channel. Research has found its effectiveness in targeting more promotions. For marketers, we need to identify other platforms (e.g., programmatic advertising, Google advertising) that also show efficacy in implementing promotional strategies—finding out and demonstrating that evidence will provide valuable suggestions to managers.

Theme 5: Pricing

Effective pricing is used to identify people's purchase likelihood towards different tailored prices. Shin and Cho (2006) proposed a response model (using support vector machine techniques) to predict the probability that a customer will respond to a promotional pricing offer. Using this model, marketers can identify a subset of customers who are more likely to react than others and adjust the pricing accordingly. Bhattacharyya (1999) also explored models in identifying the most promising customers to mail to and their most likely accepting price. Machine learning modeling is used to identify customers such that the overall profit from marketing activities, considering promotional costs, pricing, and functional costs, is maximized (Cui et al., 2006; Cui & Curry, 2005; Ghose et al., 2012). Pricing is always an interesting section in marketing studies. Dynamic pricing, which changes based on demands, supplies, customer characteristics, and external environments, gained growing popularity among AI pioneers. The most cited evidence discussing dynamic pricing also gives future scholars confidence in identifying more AI-based applications that facilitate dynamic pricing.

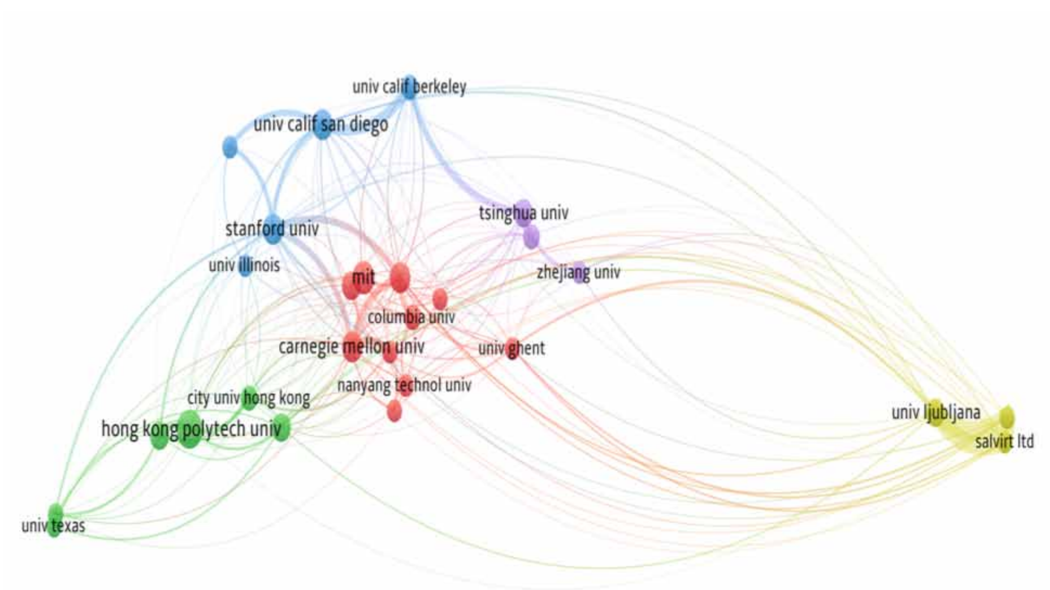
4.4 Social Network Analysis Results

Next, we conducted a social network analysis (SNA) to understand this leading research field. There are three concepts associated with social network mapping: node, edge, and cluster. The size of a node (circle) represents the frequency of the item; the edge (line) represents the relationship between items; the node's color represents the cluster; the thickness of the edge represents the frequency of two items that show together.

4.4.1 Institutional SNA

Further exploration involves analyzing the universities' collaboration network about AIM studies (as shown in figure 3). This SNA not only indicates the institutional clusters it also identifies the top universities in AIM studies. There are five clusters identified. The red cluster shows that MIT, Carnegie Mellon University, Nanyang Technology University, Columbia University, and the University of Pennsylvania have a strong collaboration network. Hong Kong Polytech University, City University of Hong Kong, and the University of Texas are another collaboration cluster (green color). California is another research concentrated region for AIM studies as Stanford University, University of California San Diego, University of California Berkeley, and University of Southern California collaborate a lot.

Figure 3. Collaboration network about AIM studies

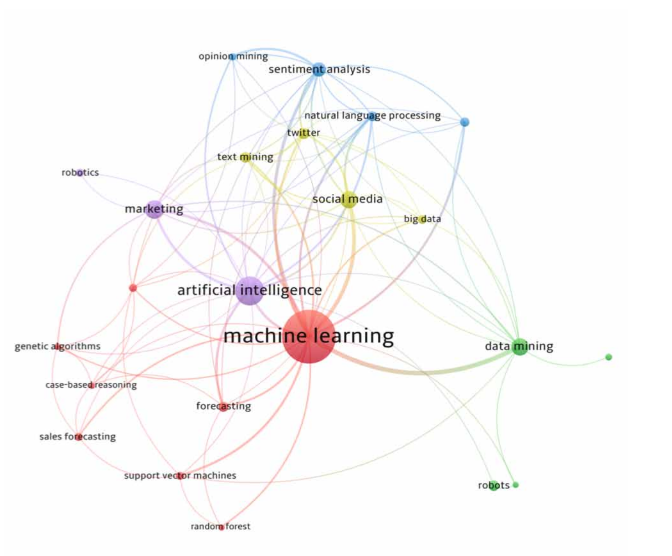


By looking deeper into each cluster, we found interesting potential research areas. For instance, Carnegie Mellon University and the University of Pennsylvania have worked on research that examines advertising content and consumer engagement on social media (Lee et al., 2018). They collected social media advertising data from Facebook and conducted a natural language processing algorithm to analyze 106,316 Facebook messages across 782 companies. The results provide strong evidence that Facebook is an effective advertising and promotion platform. Tsinghua University and the University of California, Berkeley published a paper: "Concept Clustering in Design Teams: a Comparison Between Human and Machine Clustering" (Zhang et al., 2017). This research used a machine learning approach to analyze natural language descriptions in comparing human and machine performance on clustering 1000 new product concepts. Results show that machines are good performers in identifying "over-clustering" and "under-clustering," but humans show superiorities in other tasks, such as generating creative ideas. This publication indicates that AI will not replace humans; the primary function of AI is still to augment human conversations and relieve humans from mundane tasks.

4.4.2 Keyword Plus SNA

To better understand the leading research field, we conducted a keyword analysis for the 628 published articles. It identified the most frequently used keywords on these topics. Keyword analysis can be used to identify evolving research frontiers relating to a knowledge domain. Keywords plus SNA are used to determine the most valuable keywords and reveal the citation of keywords in promising papers derived from the dataset. Figure 4 shows the keyword occurrence network. This study identifies five different color clusters.

Figure 4. Keyword occurrence network



The first cluster has major nodes associated with machine learning, classification, data mining, algorithm, and big data. This cluster emphasizes the role of big data and data analytics in revealing the data structures, characteristics, and functions in AIM research. The second cluster corresponds to the academic research activities that examined social media, sentiment analysis, natural language processing, online review, word of mouth, and sales. Actually, natural language processing, online reviews, and social media have been hot topics in digital marketing studies for a while. The third cluster is more performance-oriented, including performance, management, information, behavior, knowledge, and innovation. This cluster provides a theoretical foundation to link artificial intelligence and firm performance. Knowledge generation, innovation diffusion, and dynamic capability building could be potential paths. The fourth cluster deals with the keywords of model, algorithm, optimization, system, and design. These words are much more technical-oriented. Besides theoretical development, marketing scholars also tap into technical applications. The fifth cluster incorporates the keywords of artificial intelligence, forecasting, robotic, and marketing. The node size of artificial intelligence is relatively smaller than machine learning, but the edges that link them are thick. The popularity of artificial intelligence research is constantly growing. This suggests significant opportunities for marketing scholars.

The keywords plus SNA provides us a good picture of the current state of AIM studies and the potential theoretical foundation that links AI to marketing performance (e.g., a theory of knowledge generation, innovation diffusion, and dynamic capability building).

4.5 Main Path Analysis of the Milestone Papers

Donthu et al. (2020) show scientific works demonstrate collaborations through their references. When two articles cite the same third article, all three articles fall in a similar stream of research. Article citations form a network through which there are many influential paths. The main path is based on the importance of the citation link to identify the most significant path. The importance of each citation is measured by the number of times a citation link has been traversed if one exhausts the search from a set of starting nodes to another set of ending nodes.

Figure 5 reveals the main path and the relevant publications corresponding to the milestone papers with an arrow. It is necessary to emphasize that main path analysis is not necessarily defined by the most cited papers (Liu & Lu, 2012). In total, there are eleven milestone papers identified through main path analysis using key-routes search techniques. Figure 5 shows a clustered network in which each node represents one article, and the node size is proportional to the number of citations of this paper. The edge between the nodes means there is a citation link between these two papers. The main path network is a directed network. Each cluster indicates a research field or a theoretical stream. The main path analysis shows a total of four clusters with eleven milestone articles.

Figure 5. Main path and relevant publications by milestone

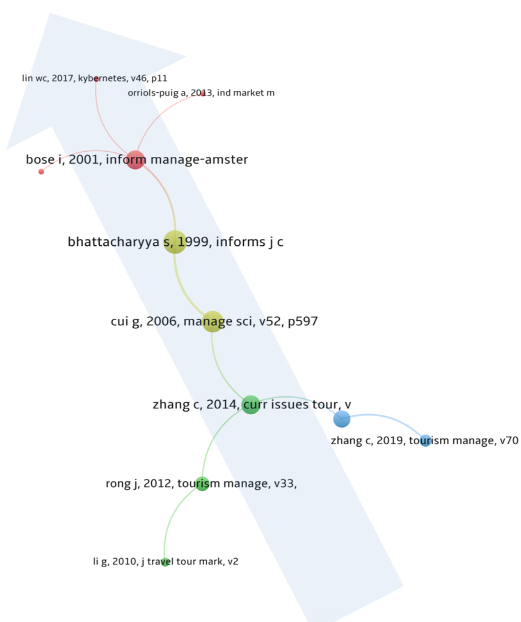


Table 6. The main path analysis documents

Cluster	Articles	Keywords	Context	Methods	Findings
Cluster 1: machine learning techniques in business such as customer relationship management, sales, publishing, online sales, and advertisement	Bose, I., & Mahapatra, R. K. (2001). Business data mining—a machine learning perspective. Information & management, 39(3), 211-225.Information & management, 39(3), 211-225.	Business applications; Data mining; Machine learning	Business	A survey of data mining applications in business is provided to investigate the use of learning techniques.	Rule induction (RI) was found to be most popular, followed by neural networks (NNs) and case-based reasoning (CBR). Most applications were found in financial areas, where prediction of the future was a dominant task category.
	Lin, W. C., Ke, S. W., & Tsai, C. F. (2017). Top 10 data mining techniques in business applications: a brief survey. Kybernetes, 46(7), 1158-1170.	data mining; business applications; machine learning; survey	Business	Examine related surveys in the literature and thus identify the frequently applied data mining techniques	There are thirty-three different data mining techniques employed in eight different application areas. Most of them are supervised learning techniques and the application area where such techniques are most often seen is bankruptcy prediction, followed by the areas of customer relationship management, fraud detection, intrusion detection, and recommender systems.
	Miralles-Pechuán, L., Rosso, D., Jiménez, F., & García, J. M. (2017). A methodology based on Deep Learning for advert value calculation in CPM, CPC and CPA networks. Soft Computing, 21(3), 651-665.	Advertisement value calculation in CPM, CPC and CPA networks; Deep Learning methods in online advertising; Sales prediction; Spam probability calculation; CTR estimation; Deep Learning in advertisement value calculation	Advertising	Based on machine learning and deep learning methods to calculate the advert value in CPM (Cost-per-mille), CPC (Cost-per-click), and CPA (Cost-per-action) networks.	DL (deep learning) is a supervised method that is very efficient in the classification of spam adverts and in the estimation of the CTR (click-through rate). In the prediction of online sales, DLNN (Deep Learning Neural Networks) have shown, on average, worse performance than cubist and random forest methods, although better performance than model tree, model rules, and linear regression methods.
	Orriols-Puig, A., Martínez-López, F. J., Casillas, J., & Lee, N. (2013). Unsupervised KDD to creatively support managers' decision making with fuzzy association rules: A distribution channel application. Industrial Marketing Management, 42(4), 532-543.	Intelligent systems; KDD; Unsupervised learning; Management support; Genetic fuzzy systems	Marketing	A novel intelligent system that incorporates fuzzy logic and genetic algorithms to operate in an unsupervised manner.	The proposed system can return a number of novel and potentially interesting associations among variables. It has significant potential to improve the analysis of marketing and business databases in practice, especially in non-programmed decisional scenarios, as well as to assist scholarly researchers in their exploratory analysis.
Cluster 2: machine learning in outbound tourism to plan more effective targeted marketing strategies.	Li, G., Law, R., Rong, J., & Vu, H. Q. (2010). Incorporating both positive and negative association rules into the analysis of outbound tourism in Hong Kong. Journal of travel & tourism marketing, 27(8), 812-828.	Contrast analysis, association rules, machine learning, data mining, Hong Kong, outbound tourism	Three large-scale domestic tourism surveys	A novel approach to data mining that incorporates both positive and negative association rules into the analysis of outbound travelers.	The negative rules provide a new tool for tourism practitioners and policymakers to understand the patterns of outbound tourism based on datasets that comprise common demographic and behavioral characteristics. The discovered negative rules can then be applied to marketing strategies, enabling costs to be reduced by avoiding the unnecessary expense of promotion to the unpromising groups of potential customers.
	Rong, J., Vu, H. Q., Law, R., & Li, G. (2012). A behavioral analysis of web sharers and browsers in Hong Kong using targeted association rule mining. Tourism Management, 33(4), 731-740.	Sharers; Browsers; Electronic word-of-mouth; Association rules; Machine learning; Data mining; Hong Kong; Outbound tourism	Tourism industry	Rule mining techniques	Young people are more likely to search for travel information and share their travel experience online than old people. Both education and income levels are found to be the key factors influencing the behavior of respondents in seeking travel-related information.
	Zhang, C., & Zhang, J. (2014). Analysing Chinese citizens' intentions of outbound travel: a machine learning approach. Current Issues in Tourism, 17(7), 592-609.	travel intention, outbound travel, machine learning, twice-learning, personal characteristic	Chinese outbound tourists	Twice-learning machine learning technique	Young people, females, and highly educated people in this life-cycle stage usually have adequate time, money and energy for leisure. This makes it possible for their long-haul travel, such as outbound travel.

continued on next page

Table 6. Continued

Cluster	Articles	Keywords	Context	Methods	Findings
Cluster 3: machine learning techniques in marketing strategies for predicting and classifying tourists.	Zhang, C., & Huang, Z. (2015). Mining tourist motive for marketing development via twice-learning. Applied Artificial Intelligence, 29(2), 119-133.	Marketing; Model	Tourism industry	Twice-learning framework	Two-phase learning process can predict tourist motives accurately as well as extract meaningful insights, which are useful for targeted marketing strategies development from the real-world data.
	Zhang, C., Huang, Z., Cao, F., & Chen, X. (2019). Recognise me from outside to inside: Learning the influence chain of urban destination personalities. Tourism Management, 70, 390-403.	Urban destination personality; Urban landscape; Overall destination image; Influence chain; Machine learning	Tourism industry	Machine learning data analysis tool	Urban destination personalities have an impact on overall destination image, and they mediate the relationship between urban landscapes and overall destination image.
Cluster 4: machine learning and modeling for direct marketing.	Bhattacharyya, S. (1999). Direct marketing performance modeling using genetic algorithms. INFORMS Journal on Computing, 11(3), 248-257.	Genetic algorithms, data mining, database marketing, profile modeling, resampling	Direct marketing	Genetic algorithm	This algorithm is effective in identifying the most promising individuals to mail to and thus maximize returns from solicitations.
	Cui, G., Wong, M. L., & Lui, H. K. (2006). Machine learning for direct marketing response models: Bayesian networks with evolutionary programming. Management Science, 52(4), 597-612.	direct marketing; Bayesian networks; evolutionary programming; machine learning; data mining	Direct marketing	Bayesian networks, neural networks, classification and regression tree (CART), and latent class regression	Bayesian networks have distinct advantages over the other methods in accuracy of prediction, transparency of procedures, interpretability of results, and explanatory insight. Our findings lend strong support to Bayesian networks as a robust tool for modeling consumer response and other marketing problems and for assisting management decision making.

Table 6 shows the eleven milestone papers in the main path analysis. Based on comprehensive content analysis, we summarized those documents into the following clusters.

Cluster 1---machine learning techniques in business: such as CRM, sales, publishing, online sales, and advertisement--- consists of four items: Bose and Mahapatra (2001); Lin et al. (2017); Miralles-Pechuán et al. (2017), and Orriols-Puig et al. (2013). This cluster compares the business effectiveness of a series of machine learning techniques (e.g., rule induction, neural networks, and supervised learning). Bose and Mahapatra (2001) and Lin et al. (2017) conducted surveys to systematically and comprehensively compare those machine learning techniques. In general, there are over thirty-three different data mining techniques employed in various business areas. Most of them are supervised machine learning techniques that are used in bankruptcy prediction, fraud detection, intrusion detection, recommender systems, and customer relationship management. Rule induction (RI) was found to be the most popular, followed by neural networks (NNs) and case-based reasoning (CBR) in financial prediction. At the same time, marketing advertising by deep learning is very efficient in classifying spam advertisements and estimating CTR (click-through rate). In predicting online sales, DLNN (deep learning neural network) has shown, on average, a poorer performance than cubist and random forecast methods. But, DLNN has demonstrated better performance than the model tree, model rules, and linear regression methods. This cluster provides a good technological foundation for researchers who want to work on AIM studies.

Cluster 2---machine learning in outbound tourism to plan more effective targeted marketing strategies--- consists of three items: Li et al. (2010), Rong et al. (2012), and Zhang and Zhang (2014). Unlike the first cluster that is more technologically oriented, the second cluster emphasizes how managers could leverage machine learning techniques to plan their marketing strategies. Those strategies include but are not limited to business planning, marketing positioning, marketing targeting, and advertising. The main managerial contribution of this cluster is that managers can take the suggestions from those papers and tailor them to their marketing activities. This cluster provides significant recommendations to practitioners and policymakers to understand the patterns of outbound tourism based on datasets that incorporate common demographic and behavioral characteristics. For instance, young people are more likely than older adults to search for travel information and share their travel experiences online. Both education and income levels are found to be critical factors that influence customers to seek travel-related information. Young people, females, and highly educated people usually have adequate time, money, and energy for leisure. The second cluster rests on the tourism industry. Rule mining techniques and a twice-learning framework are effective in cultivating customer relationships and providing customized service. This cluster offers persuasive evidence demonstrating how machine learning techniques could be used to enhance customer relationship management and the firm's selling capabilities.

Cluster 3---machine learning techniques in marketing strategies for predicting and classifying tourists--- consists of two items: Zhang and Huang (2015) and Zhang et al. (2019). The third cluster is a supplement to the second one. It also examines the role of AI in augmenting the effectiveness of marketing strategies, but the marketing strategies focus much more on predicting and classifying customers. Specifically, this cluster deals with two data limitations that happened widely in most marketing research. The first limitation is to construct a model that can generate accurate and comprehensive predictions. The second limitation is the small and noisy data collected from tourists. The two-phase learning process is found to predict correct tourist motives and extract meaningful insights from those actions. This technique demonstrates its effectiveness in effective selling and personalized advertising.

Cluster 4--- machine learning and modeling for direct marketing-consists of two items: Bhattacharyya (1999) and Cui et al. (2006). This cluster examines how to deploy AI to help the firm build a sustainable customer relationship. Because AI could directly approach and serve customers, customer relationship management has undergone a disruptive change due to applying AI tools.

5. SUMMARY AND CONCLUSION

The inaugural of AI in marketing research contained five articles annually from 1982 to 2012. Since then, the publications have grown exponentially. In 2018, the number of annual publications surged to 125, almost five times the sum of the past 30 years, suggesting that interest in the topic will continue to grow. The institutions most often affiliated with AIM studies are top research-oriented universities. Those schools include MIT, Carnegie Mellon University, Nanyang Technology University, Columbia University, University of Pennsylvania, Hong Kong Polytech University, City University of Hong Kong, and the University of Texas, Stanford University, University of California San Diego, University of California Berkeley, University of Southern California, Tsing University, and Zhejiang University.

The top 10 authors are researching AI in B2B sales forecasting, machine learning acceptance model, and machine learning knowledge generation and diffusion. Effective selling, customer relationship management (CRM), new product development (NPD), advertising and promotion, and pricing are identified by top-cited articles and main path analysis as the most common marketing activities that have used AI tools.

Effective selling, especially sales forecasting and prediction, is greatly empowered by AI tools. Research in this area can help sales managers understand how to use AI to maximize selling efforts, when and where AI might be most productive. Customer relationship management is the second field that benefits most from AI tools. AI, especially the virtual assistant and chatbot, can work like a service provider and frontline employee to increase customer-employee interface effectiveness. Research on the interaction of AI and frontline employees might provide helpful insight for marketing and sales managers. AI tools could also upgrade the new product development process. Those tools can detect the underlying mechanisms and relationships among the data to facilitate the firm's creative idea generation. Research on the use of AI in each stage of the new product development process could help shorten the new product development process, bringing products to market more quickly than competitors.

AI tools could also augment advertising and promotion. The speedy reaction and big data encompassed in AI tools enable firms to target the right customers at the right time and send them the right advertising messages. Since AI helps firms change notifications to meet customers' needs more quickly and accurately, research might examine differences in advertising appeal changes in consumer versus business markets.

Another important activity that AI tools can augment is pricing. Dynamic pricing is not a new research field. This field has been an active research stream for years, but AI tools have updated the firm's dynamic pricing capability to a higher level. AI can enable firms to automatically change the price to reflect the demand changes faster and more efficiently. Research in dynamic pricing for business markets based on AI might be useful for sales managers. Additionally, examining the effective use of AI in various pricing situations might be helpful. For example, having current pricing information about competitor products might be helpful in straight rebuy, modified rebuy, or new buy situations to quite different degrees.

In conclusion, the literature review, top authors leading publications, most cited papers, and the main path clusters show strong, informative signals for marketers to conduct high-quality research. AI is the leading force for societal advancement; with the emergence of AI, a new paradigm of the human-machine interface is on the horizon, and managers should exhibit a more open mindset to adopt AI and use it in realizing business efficiency. To make marketers and manages understand the potential advantages that AI could bring, future research could systematically review the factors that impede a firm's AI adoption, and how human intelligence (HI and AI work synergistically to improve a firm's marketing activities and its performance.

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