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RESEARCH NOTE

Exploring the Emerging Intellectual Structure in AI Marketing Publications: A Text Analysis Study

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Abstract

Purpose – This paper employs text analysis to investigate and gain a deeper understanding of the evolving intellectual structure of marketing publications on artificial intelligence.
Design/Methodology/Approach – 50 papers titled "Artificial Intelligence" and "AI" from marketing journals, published between 2009 and 2023, were used for text analysis.
Findings – Artificial intelligence-titled marketing research is in its early developmental stage. All the articles carry positive sentiments but exhibit shallow similarities. No precise key dimensions or clusters were detected. Two coherent and exclusive topics were found.
Contributions – This research employed various advanced text analysis techniques to systematically and objectively review artificial intelligence research in marketing. The results offer valuable insights into the emerging intellectual structure and the main thematic topics in literature.

KEYWORDS
Artificial intelligence, text analysis, systematic literature review, marketing, unsupervised machine learning, topic modeling, natural language processing.

1 | INTRODUCTION

Artificial intelligence, one of the most recent technological disruptors, is increasingly emerging as a popular and pivotal research topic within the business field due to its potential for producing superior value outcomes (e.g., Monod et al. 2023, Mustak et al. 2021). Artificial intelligence refers to broad techniques that enable machines to perform cognitive functions requiring human intelligence, such as learning, reasoning, planning, adapting, problem-solving, and interacting with the surroundings through higher-level autonomous knowledge creation (e.g. De Bruyn et al. 2020). As a branch of computer science, it can process proliferating information and data sources, enhance data management capabilities, design intricate algorithms, transform traditional user interactions, solve problems, and make decisions to meet real-time needs. This leads to vast applications in marketing (e.g., Haleem et al. 2022). Artificial intelligence is fundamentally reshaping marketing, management, and entire business landscapes, especially in the big data era to form a new pattern or generate new knowledge structure (De Bruyn et al. 2020, Han et al. 2021, Schiessl et al. 2022, Wilkerson and Casas 2017). Both academic researchers and business practitioners assert its centrality to the future trajectory of society. It offers enormous potential for transformative innovations in marketing, enabling exploration in consumer behavior, branding, B2B marketing, product management, pricing management, sales strategies, strategy planning, and beyond (e.g., Han et al. 2021, Schiessl et al. 2022, Wilkerson and Casas 2017).

To comprehend the current research status on artificial intelligence in marketing, scholars have employed various methodological approaches for systematic reviews. For example, Chintalapati and Pandey (2022) and Haleem et al. (2022) utilized traditional expert-based reviews. However, an increasing number of scholars have adopted relationship-based and citation-based approaches for structured literature review. Schiessl et al. (2022) used network analysis in their review. More systematic reviews now prefer bibliometric methods for artificial intelligence research in marketing, as demonstrated by Feng et al. (2021), Rosário (2021), and Verma et al. (2021). Furthermore, Wisetsri et al. (2021) and Mustak et al. (2021) have combined bibliometric methods with network analysis or topic modeling in their reviews. Vlačić et al. (2021) called for a more objective review approach to minimize subjectivity bias. They employed multiple correspondence analysis (MCA) for a systematic literature review. MCA is a hybrid-narrative approach that combines content analysis with homogeneity analysis by means of alternating least squares analysis, but this method is only for categorical variables.

Although these review articles have provided many insights into the artificial intelligence research stream in marketing, some pressing questions require further investigation. First, most of these reviews did not utilize objective data—text itself—for analysis methods. While bibliometric analysis and network analysis offer quantitative information such as citation counts, author co-occurrence, keyword co-occurrence, impact factors, publication times, and the impact and influence of specific papers, researchers, and journals (e.g., Donthu et al. 2021, Rosário 2021, Verma et al. 2021), they do not analyze text content itself but rather the historical and relational information of the publications. Consequently, popular topics and patterns identified through these methods may not align with those based on textual content. Second, previous review articles have identified very diverse topic classifications (e.g., Chintalapati and Pandey 2022, Feng et al. 2021, Haleem et al. 2022, Verma et al. 2021, Wisetsri et al. 2021), making it challenging to have convergence from all varied recommendations.

As an emerging topic in marketing, the artificial intelligence research stream is still in its early exploration stage (Wisetsri et al. 2021). At this stage, discerning clear and consistent patterns in its intellectual structure may be premature. For example, the lack of a universally accepted definition for artificial intelligence (e.g., De Bruyn et al. 2020) results in a wide range of keywords being used in article searches for reviews. These keywords include the Internet of Things, wearable technology, digital marketing, big data, and many other terms that may be partially or weakly related to artificial intelligence. In the early development stage of a field, publications are less likely to share common visions and viewpoints. The low similarity among publications causes difficulty in convergence, leading to a long list of varied suggested topics. Therefore, advanced artificial intelligence analysis methods, such as unsupervised machine learning, should be considered for systematic reviews to discover hidden structures in this new field.

This article aims to address the above research gaps by utilizing text analysis methods to investigate the intellectual structure of artificial intelligence research in marketing. When text analysis is empowered by artificial intelligence analytic techniques, its capability for quantitative examination can be dramatically expanded by efficiently handling massive volumes of objective text data (Wilkerson and Casas 2017). By automatically retrieving unstructured texts as the data source and processing it without human bias, text analysis can systematically apply predefined rules with statistical computation algorithms. Consequently, it is more likely to independently reveal less biased patterns, relationships, sentiments, and other actionable insights.

The following section reviews automated and computer-assisted text analysis as an artificial intelligence analysis method before elaborating on the specific research questions.

2 | LITERATURE REVIEW

Automated and computer-assisted text analysis can be viewed as a branch of artificial intelligence because it utilizes machine learning, natural language processing, and statistical algorithms to extract meaningful information from unstructured textual data (e.g., Moreno and Redondo 2016). Machine learning refers to a specific subset of artificial intelligence concerned with developing algorithms and statistical models to train computers to learn from data without explicit programming and enable them to analyze and interpret information for efficient problem-solving (Bhattacharya 2019). As more data is fed into the system, these algorithms continuously learn and improve their performance and accuracy, making machine learning a popular tool among academic researchers and business practitioners. While supervised learning involves researchers defining dependent and independent variables for analysis, more advanced unsupervised learning allows algorithms to find the best correlations autonomously. Natural language processing (NLP) is a founding subset of artificial intelligence that integrates computer science with linguistics techniques to analyze human language, including keyword extraction, tokenization, summarization, sentiment analysis, and more (Berger et al. 2020, Moreno and Redondo 2016).

In this study, we define text analysis as a process of utilizing linguistic, statistical, and machine-learning techniques to extract, analyze, and interpret the text for meaningful information, unraveling patterns and relationships (e.g., Carlsen and Ralund 2022, Wilkerson and Casas 2017). It can process various unstructured human communication data forms—such as academic papers, news articles, books, online content, and other historical archives—to uncover patterns, themes, topics, relationships, and sentiments. Its quantitative analysis techniques encompass a variety of methods, including sentiment analysis, supervised learning models such as classification, regression, and decision trees, and unsupervised learning models including clustering, dimensionality reduction, topic modeling, neural networks, and others. Semi-supervised learning models like keyword-assisted topic modeling also start to catch research attention (e.g., Berger et al. 2020, Carlsen and Ralund 2022, Wilkerson and Casas 2017). Supervised and unsupervised learning models have recently become the two most crucial text analysis techniques for hidden pattern discovery. Supervised learning models excel at making predictions on new, unseen data. They achieve this by learning from labeled data to predict unlabeled documents. In contrast, unsupervised learning models thrive on unlabeled data to discover hidden patterns and recognize structure by determining similarities and differences (Sharma et al. 2020). Uncovering hidden patterns is viewed as the primary strength of artificial intelligence that can autonomously create higher-degree constructs from raw data with limited or no human intervention (e.g., De Bruyn et al. 2020).

Text analysis provides several advantages for scholars conducting systematic literature reviews. First, it offers a hybrid approach between qualitative and quantitative marketing research, enabling the exploration of open-ended questions to answer the “why” like qualitative research. However, it can also permit modeling and statistical testing with scalability (Berger et al. 2020). More importantly, text analysis facilitates the discovery of unforeseen insights by allowing scholars to ask and answer questions that they did not ask or did not know the right outcome measure for the text.

Second, text analysis excels at extracting meaningful insights from vast text data, overcoming human limitations in processing information overload, and making it powerful for systematic literature reviews. Beyond identifying frequently occurring words, terms, and topics, it can detect and analyze sentiments based on extracting subjective information from unstructured text content (Wankhade et al. 2022), allowing us to understand the valence of the author's attitudes—such as positive, negative or neutral.

Third, text analysis fosters a more objective and systematic evaluation of existing knowledge within a field (Mustak et al. 2021). Its ability to scrutinize and synthesize vast amounts of text data makes it a powerful tool for uncovering the intellectual structure of a domain. By identifying key topics and trends, the discovered hidden patterns can guide future research efforts with a targeted focus.

This research leverages text analysis to address critical questions that will help us unravel the knowledge structure of artificial intelligence research in marketing. Our research questions include: What are the top terms used in artificial intelligence-titled marketing publications? What are their similarities, overall sentiments, key structural dimensions, and emerging common topics? We also explore the relationship of these topics with relevant covariates such as journal quality levels and publication year.

In the following sections, we apply text analysis to a systematic review of artificial intelligence research in marketing to gain a deep understanding of the intellectual structure of this research stream. To ensure research validity and avoid biases, we adopted all the steps suggested for text analysis and systematic review (Denyer and Tranfield 2009, Lucas et al. 2015, Wilkerson and Casas 2017).

3 | RESEARCH METHODOLOGY

3.1 | Data collection procedure

All the data were collected from the ABI/Inform Complete database, which is available through the library website. This database is widely regarded as a valuable resource for business research and academic studies, providing access to comprehensive scholarly journals, dissertations, working papers, trade publications, market reports, and more. PDF files of artificial intelligence-titled marketing publications were downloaded as raw text data. Previous reviews have included numerous terms as keywords for artificial intelligence, such as machine learning, robot, automation, big data, neural networks, text mining, soft computing, fuzzy logic, geotagging, biometrics, wearable, Internet of things, and others (e.g., Mustak et al. 2021). However, many of these terms do not necessarily represent artificial intelligence. Unlike previous research, this study exclusively focuses on artificial intelligence as the keyword. Thus, only two keywords are used in the query: "artificial intelligence" or "AI" in the fields of "title" or "abstract," with "journal of marketing" specified in the field of publication title. Any editorial articles, systematic reviews, and bibliometric analyses mentioned in the literature review were included in our sample. Moreover, the search was also confined to "peer-reviewed" academic journal articles with "full text" in the subject areas of "Business, Management, and Accounting," without any year limitation, but excluding wire feeds. Finally, metadata for these artificial intelligence-titled marketing articles was retrieved, including publication year, journal name, and journal quality level.

We assessed journal quality at three different levels. The journals on the Financial Times' top 50 were labeled "high quality." Those not included in the Financial Times' top 50 list but listed as A* journals in the 2022 Australian Business Deans Council (ABDC) Journal Quality List were labeled "medium quality." Journals not falling into either category were labeled as "low quality." However, we elevated one journal—the Journal of Business & Industrial Marketing—to a medium level. Since 2019, this journal has consistently demonstrated editorial commitment to Artificial intelligence with high-quality publications on this topic. Our search yielded 50 publications from 13 journals across three different quality levels from 2009 to 2023. Among these publications (see Table 1), three high-quality articles are all from the Journal of the Academy of Marketing Science. Seventeen articles appeared in medium-quality journals, originating from the European Journal of Marketing and the Journal of Business & Industrial Marketing. Thirty articles were sourced from low-quality journals (e.g., Academy of Marketing Studies Journal, Journal of Financial Services Marketing). This distribution suggests that artificial intelligence research is still in its early stages of development, and researchers face challenges in publishing articles on this topic in top-tier marketing academic journals.

We followed established protocols for data preparation, importing text, coding data, tokenization, preprocessing, and various data analysis techniques (e.g., Carlsen and Ralund 2022, Wilkerson and Casas 2017). We used R statistical software for text analysis due to its extensive range of text analysis packages, such as speedReader, readtext, stringi, quanteda, tidytext, textplot, ggplot, stopwords, dplyr, stm, and others (Welbers et al. 2017).

3.2 | Preprocessing methods

It is vital to employ various methods for the preprocessing specification because 50 journal publications from 13 different journals with three different quality levels from 2009 to 2023 can contain substantial amounts of meaningless information. Removing punctuation, stopwords, symbols, URLs, separators, and numbers, as well as using stemming and lowercasing, helps eliminate noise and allows for focus on the essential words, terms, and content.

For the preprocessing method, we used Quanteda to tokenize the documents by removing punctuation, symbols, numbers, URLs, and

TABLE 1 Journal Names and Their Quality Levels.

Journal Name	Quality Level	# of Publications
J of Database Marketing & Customer Strategy Management	Low	1
International J of Bank Marketing	Low	3
J of Financial Services Marketing	Low	1
J of Research in Interactive Marketing	Low	4
Academy of Marketing Studies J	Low	12
J of Services Marketing	Low	3
J of Consumer Marketing	Low	2
J of Islamic Marketing	Low	1
J of Marketing Development and Competitiveness	Low	1
Spanish J of Marketing	Low	2
European Journal of Marketing	Medium	12
J of Business & Industrial Marketing	Medium	5
J of the Academy of Marketing Science	High	3

separators before lowercasing, stemming the terms, and removing stopwords. In the end, the data contained 589,100 tokens for this text analysis.

To further clean and refine the text and find critical words and terms in the unstructured text, we preprocessed the documents using several methods: removing punctuation, stopwords, symbols, URLs, separators, and numbers, stemming, and lowercasing. Using 'topfeatures()' function, we also used a customized stopword list to get rid of some meaningless frequent words such as "the," "and," "of," "to," "in," "a," "is, "that," "et," "as," "on," "with," "are," "journal," "vol," "pp," "can," "al," etc.

After preprocessing by removing punctuation, symbols, numbers, URLs, and separators and converting text to lowercase, the corpus contains 24,070 features with 92.46% sparsity. Subsequent stemming of the words reduced the features to 23,939, with 92.79% sparsity. After removing English stopwords, the features were further reduced to 18,668, with 92.69% sparsity. Finally, after removing custom stopwords, the corpus contained only 18,649 features, with 92.73% sparsity. Therefore, the unique features were reduced and purified with each preprocessing step, while the sparsity remained almost unchanged.

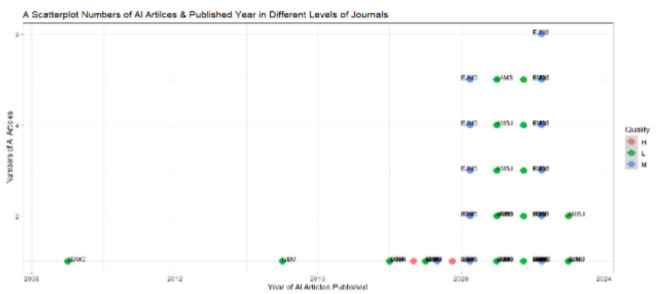

FIGURE 1 Number of publications per year on artificial intelligence-titled marketing publications

FIGURE 2 Word cloud chart based on frequency count

4 | RESEARCH RESULTS

4.1 | Descriptive statistics

Among the 50 artificial intelligence-titled marketing publications, the first article was published in 2009 and the most recent in 2023. Notably, there is a significant gap after the first paper, with the second article not appearing until 2015 (see Figure 1). Publication numbers remained relatively low until 2022, with only 3, 5, 8, and 10 articles published in 2018, 2019, 2020, and 2021, respectively. However, this trend changed dramatically in 2022, with the number of publications jumping to 19. This increase underscores the growing interest in artificial intelligence-titled research within marketing academic publications.

A word cloud chart can visualize the most prominent semantic content within the text by varying sizes of word frequency. Our word cloud chart (see Figure 2) identified "marketing," "AI," "research," "intelligence," "technology," "information," "consumers," "service," "business," and "digital" as the top 10 keywords that appeared in these 50 artificial intelligence articles.

Moreover, a Lexical Dispersion Plot was performed to assess the frequency of three keywords, "AI," "artificial," and "learning," in each article based on their word frequency counts (see Figure 3). Additionally, Figure 3 illustrates the locations within each article where these words appear. Consequently, "AI" emerges as the most heavily used

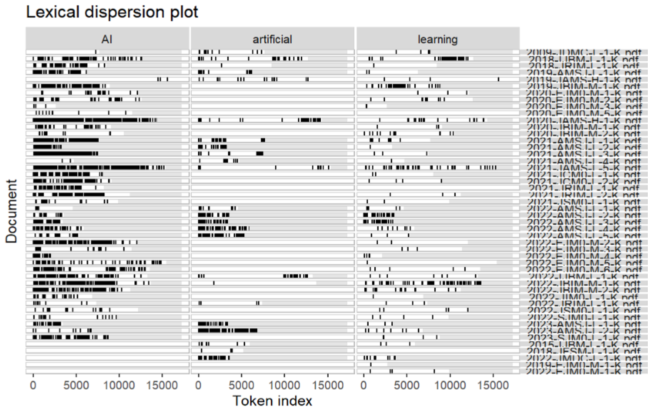

FIGURE 3 Examples of How Key Words Appeared in Each Article

word among the three terms, appearing much more frequently at the beginning rather than at the end of each article.

4.2 | Sentiment Analysis

We used the 2015 Lexicoder Sentiment Dictionary integrated into Quanteda to calculate the valence of the documents in our corpus. The results for overall sentiment in these 50 artificial intelligence publications (see Figure 4) indicated that almost all the articles carry positive sentiment. However, the magnitude of this positive sentiment decreased around 2020 during the Pandemic, increased again around 2021, but declined again in 2022.

Such drops might signify a potential "AI winter" attributable to various challenges in artificial intelligence, such as the absence of emotions, common sense, and transferability, as well as the low success rates in implementing AI systems (e.g., De Bruyn et al. 2020, Lissillour and Monod 2024, Monod et al. 2023). Negative sentiments may escalate as potential issues and concerns emerge during AI development and implementation. For instance, while AI systems are intended to aid employees, their deployment may tip the balance of power toward greater management control or substitute the employee perspective, leading to devaluating employees' work practices. Discrepancies between the design and implementation stages may cause transparency issues and power struggles within the organization, resulting in employee disappointment and resistance to AI applications (Lissillour and Monod 2024, Monod et al. 2023).

4.3 | Similarity Analysis

Checking the content similarity among all the publications provides crucial insights into the structural overview of the knowledge field. We used two reference points to compare the similarities among the 50 artificial intelligence-titled articles: one high-quality article and one low-quality journal. We aimed to determine whether each article is more

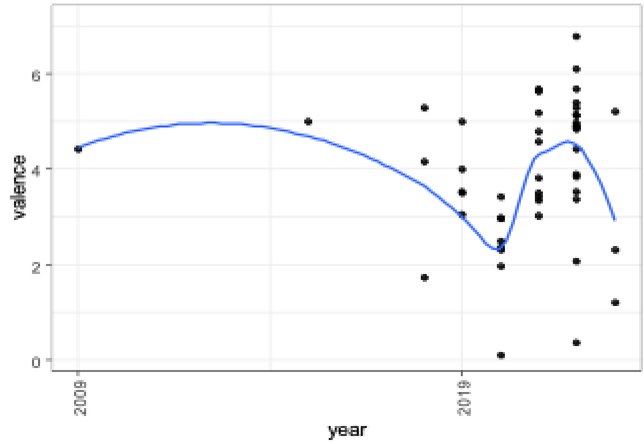

FIGURE 4 Sentiment Analysis Results

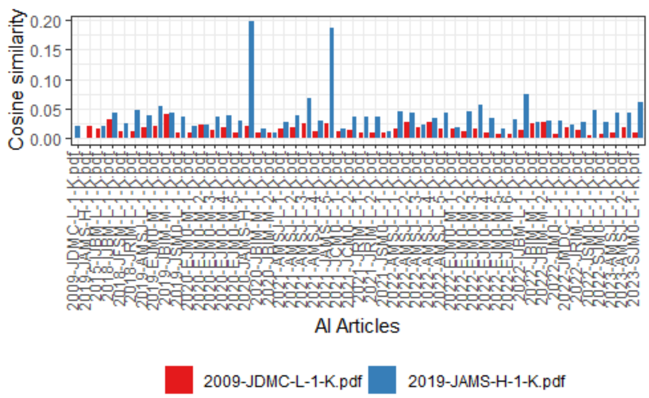

FIGURE 5 Cosine Similarity Analysis Results

similar to the high-quality or the low-quality paper based on text content. We selected the first paper published in 2009 in a low-quality journal as the low-quality reference. Among the three top-quality journal articles, we chose one published in 2019 to represent high quality. All other papers were compared with these two references. To address issues of term frequency imbalance in text content, the TF-IDF method was used to highlight the importance of terms with discriminatory power, allowing control over word popularity and document length. Thus, using the TF-IDF method improved the effectiveness of cosine similarity.

The cosine similarity test results (see Figure 5) indicated that all the papers are more similar to the high-quality reference from 2019 than the low-quality one from 2009. The LSA package in R provided a direct cosine similarity value of 0.0197, indicating a very low similarity of the articles.

To better visualize the similarity among all 50 articles, a heat map (see Figure 6) was created based on cosine similarity scores. The prevalence of very light colors in the map indicates the overall low similarities

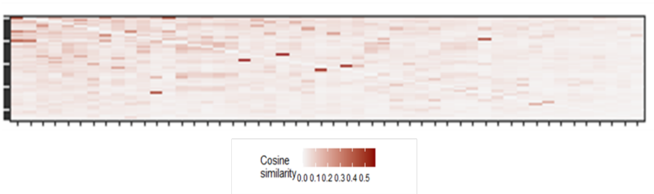

FIGURE 6 Heat Map Analysis Result

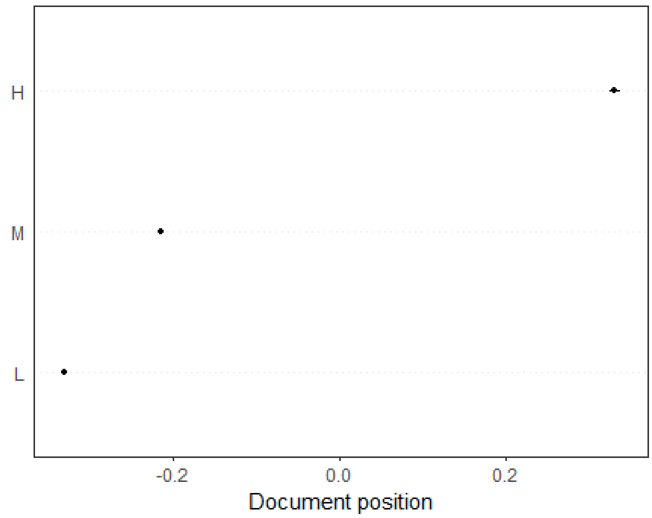

FIGURE 7 Scaling Model with Wordscores Analysis Results

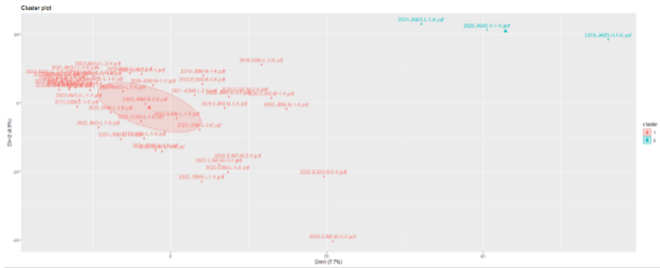

FIGURE 8 Unsupervised Learning Results: K-means Clustering Results

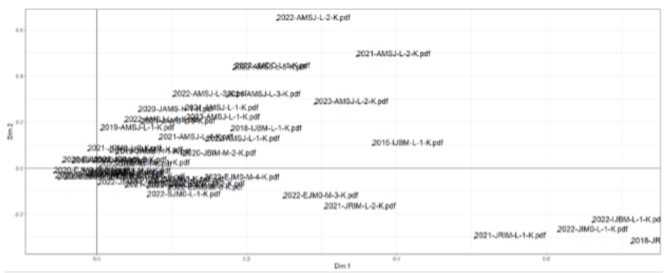

FIGURE 9 Unsupervised Learning Results: PCA Method

among the 50 artificial intelligence articles, consistent with the cosine similarity analysis results.

The following important research question is how similar these articles are across different quality journal levels, based solely on each article's text content. The wordscores scaling model can quantify and compare texts on a specific dimension without relying on complex feature spaces in document-level similarity/distance metrics. We used the wordscores method to align the corpus with the dimensions of the low-quality and high-quality journal articles. The results, shown in Figure 7, indicate that high-quality journal articles are much more dissimilar from low- and medium-quality journal articles.

4.4 | Unsupervised learning models

Unstructured textual data presents challenges due to its high dimensionality, noise, and irrelevant features. Unsupervised learning uses techniques such as clustering, dimensionality reduction, and topic modeling to unravel hidden patterns within data. Clustering groups data points based on similarities, while the dimensionality reduction technique reduces complexity and noise by focusing on critical features to improve model performance and obtain effective interpretable models (Underhill et al. 2007).

We chose K-means clustering analysis for clustering and Principal Component Analysis (PCA) for dimensionality reduction. When we performed the PCA analysis, a TF-IDF weighting was used to highlight the importance of the term. We experimented with different numbers of dimensions (5, 3, and 2) in both K-means clustering and PCA. However, consistent results across methods (see Figures 8 & 9) indicated a lack of clear patterns in the data, even with k=2 for the PCA method capturing the most variance. It aligns with the understanding that observing distinct structures or patterns in this field may be too early. Figure 8 highlights notable differences between three high-quality journal articles and those from low- and medium-quality journals. This observation is consistent with the typical delay in top journals publishing papers from emerging fields.

We performed different types of topic modeling to explore topics within artificial intelligence-focused marketing research. Topic modeling provides a straightforward approach to analyzing extensive unstructured text data, facilitating the association of words with similar meanings and discernment among those with diverse and multiple meanings, thereby unveiling the concealed thematic structure within textual content (George and Birla 2018). It enables the identification of topics receiving the most research attention, the detection of underlying thematic trends, and the retrieval of the most relevant documents for each topic. Traditional topic modeling methods such as Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA) primarily concentrate on revealing latent topics within a text corpus based on word co-occurrence patterns (George and Birla 2018). However, the Structural Topic Model (STM) extends this approach by integrating document-level metadata as covariate integration to elucidate topic-covariate

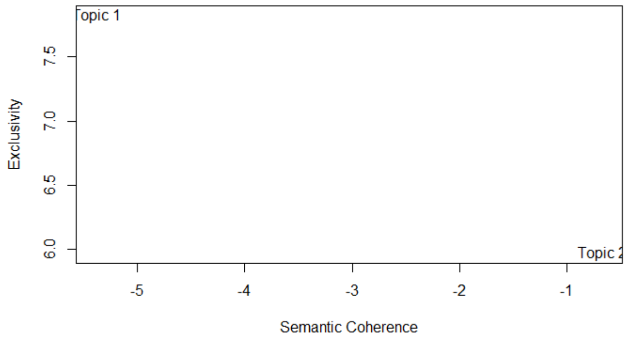

FIGURE 10 Exclusivity and Semantic Coherence Test on Topics

contextual relationships (Grajzl and Murrell 2019, Sharma et al. 2021). Before undertaking structural topic modeling, we removed additional infrequent and frequent terms in the preprocessing stage. To identify reasonable topical groupings, we initiated the model fitting with k=5. Ultimately, we uncovered two dominant and noteworthy topics (see Table 2). Four methods (Highest Prob, FREX, Lift, and Score) provided potential top words in each topic. These methods utilized various metrics, such as highest probability, frequency, exclusivity, the ratio of probability across all topics, and a combination of the previous three. After combining and balancing the results from the other three methods, the Score method listed “religio, asia, bank, servit, checkout, mobil” as the top words for the first topic, and “regression-typ, tweet, restraint, bnd, dictionary, computer-aid, cluster” as the top words for the second topic. After making sense of all the top words within and across the two topical contents, we named the first “AI applications across various industries” and the second “AI with marketing research.” We performed an additional examination to assess the quality of the topics (see Figure 10). High-quality topics should maximize exclusivity and semantic coherence, implying that the top words are sorted into well-defined groups with coherent co-occurrence within a given group. The results in Figure 10 demonstrated that these two topics possessed high quality in terms of both their exclusivity and semantic coherence. Moreover, for a robust check, we conducted LDA topic modeling, and the results validated these two topics as the sole choices emerging from analyzing 50 artificial intelligence-titled marketing publications over the past 14 years.

Lastly, we incorporated quality levels and publication years as covariates to address two critical research inquiries: Has each topic been equally studied across different quality levels of journals? Is there a topic shift across time? Our findings showed that journal quality levels and publication years exhibited no significant relationship with these two topic choices. However, topic 2 received more attention over time compared to topic 1.

5 | CONCLUSION

This research employed text analysis to quantitatively examine artificial intelligence-themed marketing publications over the past 14 years. As a pioneering effort in using various text analytics techniques, this review distinguishes itself from previous ones by its objectivity, robustness, structure, and comprehensiveness. Our systematic review yielded the following essential insights into the evolving intellectual structure of this nascent field.

Our analysis revealed the top ten keywords prevalent in the field: marketing, AI, research, intelligence, technology, information, consumers, service, business, and digital. Our results differ from those of Mustak et al. (2021) in that “AI” and “intelligence” are not among their top words. Most other review papers used overly broad keywords to search and build their data, making those reviews less relevant to the AI topic than this research. Despite the breadth of publications, only minimal similarities were found among the 50 publications analyzed. Notably, articles from high-quality journals differed significantly from those in low- and medium-quality journals. Most publications resemble recent high-quality articles more than older, low-quality ones. This suggests a dynamic evolution within the field, with limited common ground among current publications.

Secondly, sentiment analysis indicated a predominantly positive tone across articles, albeit with a decline in magnitude around 2020. None of the systematic review papers studied in this study have provided a sentiment analysis of the literature. Such a drop around 2020 reminds both researchers and practitioners that various pitfalls of artificial intelligence (such as lack of emotions, common sense, transferability, and more) may occur during the AI development and implementation process (e.g., De Bruyn et al. 2020, Lissillour and Monod 2024, Monod et al. 2023).

Lastly, we identified two primary topics through structural topic modeling: AI applications across industries and AI with marketing research based on objective text content. These two topics exhibited high exclusivity and semantic coherence, with consistent coverage across journals with varying quality levels and no shift over time. However, the latter topic received more examination over time. Our topics are very different from those of other review papers. For example, Mustak et al. (2021) identified ten salient research topic themes, but five related to consumers: consumer sentiments, customer satisfaction, customer loyalty and trust, and customer relationships. However, these topic themes heavily overlapped and lacked exclusivity and semantic coherence. Our two core research topics are more objective and underscore the current actual state of the field.

While this research aimed to conduct an objective systematic literature review through text analysis, our selection of keywords and the coverage of the subscribed database (ABI/Inform Complete) restricted our findings. Moreover, we excluded ongoing and unpublished knowledge or articles without full texts in the database. Future research should consider broadening the keywords and including additional databases

TABLE 2 Unsupervised Learning Results from Structural Topic Model.

Highest Prob: Metric gives words that have the highest probability of appearing in a particular topic
FREX (Frequency and Exclusivity): FREX is a measure designed to find words that are both frequent and exclusive to the topic
Lift: Lift refers to the ratio of a word's probability within a topic to its marginal probability across all topics
Score: Score is a combination of the above metrics and balances both the frequency and exclusivity of words in a topic

Topic 1's Top Words	Topic 2's Top Words
Highest Prob: servic, consum, bank, ai, use, research, technolog	**Highest Prob:** market, ai, custom, use, data, research, intellig
FREX: aisa, bank, mobil, checkout, smart, speaker, intent	**FREX:** b2b, tweet, artifici, code, socialbot, crm, dictionari
Lift: ai-context-specific, arc, ave, belanch, belli, boot, bootstrap	**Lift:** churn, cluster, negoti, restraint, #blackfriday, #buynothingday, adida
Score: religio, aisa, bank, servit, servic, checkout, mobil	**Score:** regression-typ, tweet, restraint, bnd, dictionari, computer-aid, cluster
Topic 1: AI's Applications Across Different Industries	**Topic 2: AI with Marketing Research**

to ensure a more comprehensive, complete, and relevant sample text analysis.

As a pioneering study, we were uncertain about how to apply more advanced text analytics techniques to our study. Future marketing research, including systematic reviews, should prioritize using text analysis as a research methodology. Embracing more sophisticated artificial intelligence-based research methods could significantly enhance the research quality and increase the likelihood of publishing AI-themed marketing research in leading marketing journals. However, researchers need to exert significant effort to publish core AI-themed articles in top-tier journals. This effort may include developing suitable measurements to reflect a firm's core strategies and investment in artificial intelligence, identifying proper theory, building attractive theoretical models, and collecting real-world AI performance data. Looking ahead, the field would greatly benefit from an influx of conceptual papers to inspire creative AI research ideas and guide future research endeavors during the early development stage.

While our sentiment analysis indicated a decline in positive attitudes toward artificial intelligence around 2020, our study could not provide details to address the concerns in this emerging field. As a new and potentially disruptive technology, artificial intelligence's development and implementation process requires proper governance. Before AI advances, future academic research must explore appropriate legal regulations, ethical standards, and governance mechanisms to prevent and mitigate potential disruptions and harm to humans and society. Establishing guidelines, regulations, and frameworks can ensure that new artificial intelligence technologies are developed ethically and deployed responsibly.

AUTHOR CONTRIBUTIONS

The author contributed to the conceptualization, data collection, writing, data analysis, reviewing and editing of the manuscript.

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FINANCIAL DISCLOSURE

None reported.

CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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SUPPORTING INFORMATION

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