AI on AI: Unveiling Trends and Patterns in AI in Marketing Using Large Language Models

Faridoddin Rezaei
University of Bremen
Maik Eisenbeiss
University of Bremen
Kristina Klein
University of Bremen

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This study explores the application of artificial intelligence (AI) in marketing by addressing several research questions concerning patterns in marketing elements, methodologies used, and AI domains. Using a knowledge discovery in databases (KDD)-based methodology, the study employs Large Language Models (LLMs) to screen a dataset of over 300,000 papers, thereby significantly enhancing the depth and efficiency of the literature review process. Filtering identifies more than 9,000 relevant studies. We analyze those papers with the support of LLMs to uncover patterns of AI applications in marketing. The study's primary contribution lies in demonstrating the transformative potential of LLMs in conducting large-scale literature reviews, setting a new benchmark for research synthesis in rapidly evolving fields. Findings reveal rising trends such as a growing focus on relationship and consumer-focused solutions elements, alongside the sustained dominance of consumer, behavioral influence, and decision making.

Keywords: Artificial Intelligence, Large Language Models

Track: Methods, Modelling & Marketing Analytics

1 Introduction

The integration of Artificial Intelligence (AI) into marketing has transformed practices, in both research and industry (Mirwan et al., 2023; Priyanka et al., 2023). The global AI in marketing market is projected to grow from USD 12.5 billion in 2022 to USD 72.1 billion by 2030 (Logidots, 2021; Zion Market Research, 2023). For instance, Netflix's AI-powered recommendation engines, which save over USD 1 billion annually through personalized content suggestions, demonstrate AI's profit potential.

On the research front, a Scopus search in late 2024 revealed over 300,000 studies on AI and marketing, with notable growth since 2013. To get an overview on the topics investigated and to learn from what previous research, extensive reviewing of the existing literature is necessary. Some literature reviews attempt to cover the field and to present a cohesive and comprehensive understanding (Chintalapati & Pandey, 2022; Mustak et al., 2021; Ngai & Wu, 2022; Oueslati & Ayari, 2024; Vlacic et al., 2021; Ziakis & Vlachopoulou, 2023). However, these reviews typically encompass only a few hundred to 1,000 studies, sometimes limiting the number of included papers by restricting their search to selected journals and/or using a narrow set of general keywords such as "Artificial Intelligence" or "Machine Learning". Studies like the one by Mariani et al. (2021) gather a broader number of papers, but rely solely on initial search results without implementing further filtering (screening) steps. Focusing exclusively on top-tier publications heightens the risk of neglecting significant studies (e.g, by lesser-known scientists in prominent journals)(Singh et al., 2007), particularly given the interdisciplinary nature of AI in marketing and its rapid advancements. Additionally, some research, such as the one by Tsilingeridis et al. (2023), Habbat et al. (2023), Liu et al. (2021), and Li et al. (2023), may not explicitly mention "Artificial Intelligence" or "Machine Learning" in their titles or abstracts. However, these works delve into specific subdomains of AI, highlighting the need for search using a broader spectrum of keywords considering the diverse terminologies employed within AI. Moreover, relying solely on initial search results without further filtering risks incorporating irrelevant studies, potentially compromising the accuracy and reliability of the findings. The sheer volume and continuous growth of studies make it impractical for individuals to conduct and up-to-date literature reviews manually, even with expert assistance.

Modern tools like Connected Papers LitMaps (LitMaps, 2024) simplify finding related studies by analyzing citation networks and visualizing relationships between papers. AI-driven tools such as UnderMind (UnderMind, n.d.) and Elicit (Elicit, 2024) enable natural language searches and provide summaries. While these tools enhance efficiency in locating and reviewing individual papers, they fall short in conducting comprehensive literature reviews, leaving synthesis and detailed analysis largely reliant on manual effort.

The overarching goal of this study is to review the vast literature on AI in marketing, leveraging the capabilities of Large Language Models (LLMs) to perform an extensive and in-depth analysis. The methodological approach helps to identify, manage, and interpret the increasingly large volumes of existing research and to provide a comprehensive synthesis. LLMs are effective in handling and analyzing text data, including topic identification and information extraction (Zhao et al., 2023). This project aims to extract and distill key information from a multitude of databases to address key questions. These key questions include:

- Which marketing elements in research on the use of AI in marketing have been most extensively explored, and which remain largely unexplored? Additionally, what are the past and current trends in this area?
- Which AI domains are most explored, and which research methodologies are most commonly used currently? How do these differ from the past?
- What are the intersections of these insights, such as which AI domains are being used in conjunction with specific marketing elements?

2 Selected Insights from Prior Literature

2.1 AI focus in marketing research: a look at literature reviews

Several literature reviews offer insights into which domains of marketing research receive the most attention regarding AI applications. A study by Mustak et al. (2021) identifies ten prominent themes, with a focus on understanding consumer sentiment, customer satisfaction, and market performance through AI. These findings suggest a strong emphasis on leveraging AI for customer insights and using this as a starting point to optimize marketing strategies. Another review by Ziakis and Vlachopoulou (2023) explores AI's impact on digital marketing specifically. Their analysis revealed distinct clusters like social media, consumer behavior, and digital advertising, highlighting the prevalence of AI applications in these areas. Additionally, Vlacic et al. (2021) outline several key domains within marketing that focus on the use of AI, including marketing channels, marketing strategy, performance enhancement, and segmentation, targeting, and positioning. This research underscores AI's broad application across various marketing functions, from operational efficiency to strategic decision-making and performance improvement. Oueslati and Ayari (2024) utilize bibliometric analysis to evaluate the scientific output on the topic of AI in marketing. They analyzed a screened dataset of more than 700 papers. Their work identifies ”customer service,” ”security applications,” and ”market segmentation and consumer insights” as well-researched areas. Emerging topics highlighted include ”ethical considerations,” ”AI in strategic marketing decisions,” and ”interdisciplinary applications.” While these reviews provide useful insights, reviewing a larger volume of studies captures the evolving nature of AI in marketing and integrates interdisciplinary perspectives from fields like computer science, psychology, and business for a more comprehensive analysis.

2.2 Methodologies employed in previous AI-driven literature reviews: the rise of LLMs

While literature reviews are crucial for summarizing knowledge, identifying gaps, and providing context (Baumeister, 2013), the traditional process can be time-consuming and may result in outdated findings once the review is finally published (Felizardo et al., 2014). Recent advancements in AI, particularly LLMs, offer promising solutions to these challenges.

For instance, Alshami et al. (2023) used LLMs to filter and categorize articles from Scopus, demonstrating that ChatGPT 3.5 performs well in identifying relevant papers. Similarly, Syriani et al. (2023) found that ChatGPT 3.5 Turbo’s performance in systematic review screening was comparable to traditional machine learning classifiers, without requiring extensive domain-specific training. However, its classification accuracy was insufficient to fully automate the process, highlighting the need for better prompting techniques and setups.

A recent preprint by Joos et al. (2024) evaluated multiple LLMs, including open-source and commercial models like GPT-4o, during the screening phase of a systematic literature review on approximately 8,000 papers in computer science. Their dual approach, combining automated methods with manual verification, achieved high recall (>98%) and accuracy (up to 99.3%). This study highlighted the importance of combining multiple models, refining prompts, and incorporating human validation to improve results further. In comparison to those rates, Gartlehner et al. (2020) reported human reviewer sensitivity and specificity as 86% and 79.2%, respectively. While different in setup, these findings suggest that LLMs can significantly enhance filtering in literature reviews. These studies used LLMs only in the screening phase with limited scope and are not focused on AI applications in marketing. To the best of our knowledge, no literature review, even in the broader domain of marketing, leverages LLMs, highlighting a gap for a comprehensive approach that fully utilizes their potential

3 Methodology

The methodology of this study adheres to the Knowledge Discovery in Databases (KDD) process outlined by Fayyad et al. (1996), encompassing the phases of selection, preprocessing, transformation, data mining, interpretation, evaluation, and knowledge presentation.

Figure 1 illustrates the adapted KDD process, highlighting the interconnections among the phases that collectively structure the methodology. We will provide detailed descriptions of each phase in the subsequent sections.

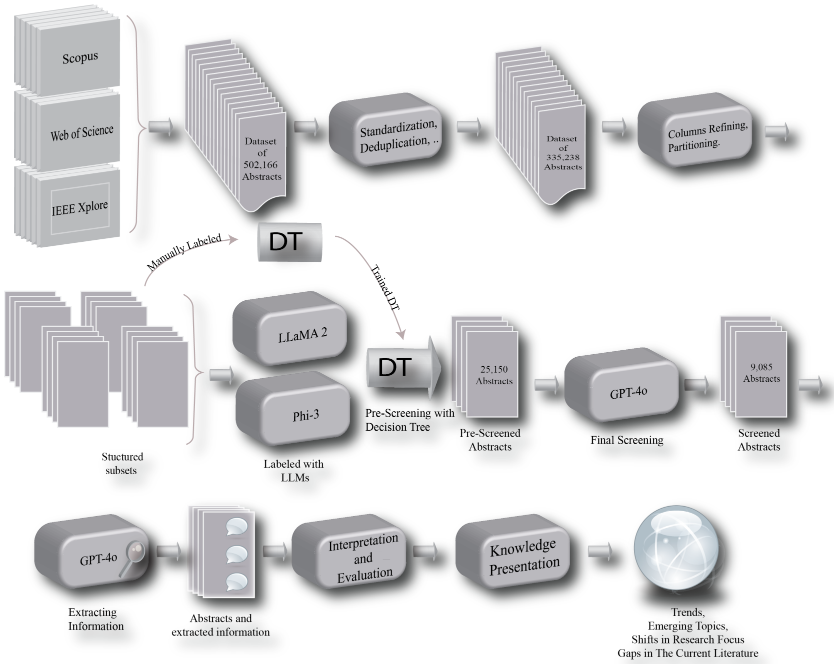

Figure 1: Flowchart illustrating the KDD process adapted for this study.

3.1 Selection and preprocessing

The research begins with extensive data collection from Scopus, IEEE Xplore, and Web of Science, selected for their comprehensive repositories of peer-reviewed articles across disciplines. Scopus covers marketing and technological innovations, IEEE Xplore focuses on AI advancements relevant to marketing, and Web of Science provides an interdisciplinary outlook. Using 23 keywords, including marketing, consumer, AI, and machine learning, combined with Boolean operators, the search spans from 2013 to mid-November 2024, resulting in a dataset of 502,166 papers. The preprocessing phase ensures consistency across datasets by standardizing formats, concatenating datasets, and assigning unique identifiers. Data cleaning involves removing documents without abstracts and applying a dual-stage deduplication process (Duhamel et al., n.d.), refining the dataset to 335,238 papers.

3.2 Transformation

3.2.1 Filtering with LLMs

In traditional literature reviews, human experts screen and filter papers to determine relevance. In this study, AI replaced human reviewers, leveraging multiple models (raters) to cross-verify data and enhance validity (McHugh, 2012). We used the LLaMA 2-13B and Phi-3-medium-4k-instruct models simultaneously. Using a predefined prompt, refined through several trial-and-error iterations to achieve the best format, these models assess each abstract's relevance to AI applications in marketing, classifying them as "Yes," "No," or "Somehow".

Manual labeling:: A dataset of 340 abstracts was randomly selected for the initial labeling phase. Both LLaMA 2 and Phi-3 assigned labels, while one of the authors manually labeled each abstract as 'Related' or 'Not related' to create a reference dataset for training the decision tree. The decision tree was employed to better align the filtering results generated by the LLMs with human expert judgment.

Dual-model and decision tree: A decision tree algorithm was employed to integrate and analyze the labels from LLaMA 2 and Phi-3. A training dataset of 240 abstracts was used, with manual labels as the dependent and LLM labels as independent variables. The remaining 100 abstracts formed the validation dataset, where the decision tree achieved a specificity of 0.83 and a sensitivity of 0.86. To further enhance the evaluation process, two additional stages were introduced.

Application of the decision tree to large-scale data: The trained decision tree was configured for very high specificity (100%) to ensure inclusion of the potentially most relevant papers, even at the risk of false positives. This filtering narrowed the dataset to 25,150 papers.

Final screening: In the final screening phase, ChatGPT-4o, known for its high sensitivity and specificity (Joos et al., 2024), processed the 25,150 abstracts. This step refined the dataset to 9,085 papers related to the use of AI in marketing, excluding non-pertinent papers.

3.3 Data mining

In the data mining phase, we utilized ChatGPT-4o to process the screened abstracts, enabling the extraction of information based on contextual understanding. Prompts were designed to gather details on three aspects of each paper: (1) marketing elements addressed, (2) research methodologies used, and (3) AI domains applied. Prompts were refined through a trial-and-error process to ensure accuracy and consistency in the desired format. For marketing elements, the prompt was designed to select from predefined categories, including marketing mix elements (product, price, place, promotion, people, process, physical Evidence) and extended marketing concepts (consumer, cost, convenience, communication, consumer-focused solutions, value, segmentation, targeting, positioning, brand, behavioral influence, relationship, service, sales, marketing in general, decision making). The extracted information was saved for each paper.

3.4 Evaluation

To ensure the reliability and accuracy of the entire model, a validation procedure is underway. Two students are screening a randomly selected subset of the main dataset. For each paper, they answer questions about marketing elements addressed, research methodologies, and specific AI domain used. Their answers will then be compared with the authors' screening and answers to the same questions. Discrepancies will be resolved in mutual meetings. The resulting dataset will be used to validate the entire model and to calculate validation measures.

3.5 Knowledge presentation

To address the first research question regarding the explored marketing elements and trends over time, a time series line chart (Figure 2) was created for marketing elements from 2013 to 2024. The chart focuses on elements more commonly used. Numbers are normalized by the total number of studies per year to account for variations in study volume, showing trends in element usage. Since each study could include up to three elements, total normalized values can exceed 1. This chart serves as a sample of the broader analysis conducted in the study.

The analysis of trends in marketing elements reveals several key patterns: **Rising elements** include relationship and consumer-focused solutions, reflecting a growing focus on building long-term customer connections and meeting specific consumer needs in AI-driven marketing. **Central elements** such as consumer and behavioral influence remain dominant and stable over time, highlighting their ongoing importance. **Less commonly used elements** like promotion, price, and brand have remained consistently present at low levels.

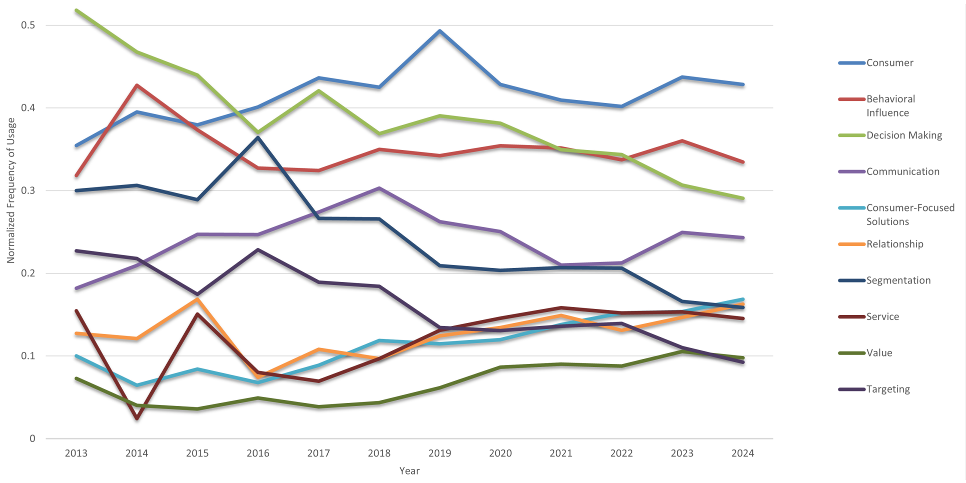

Figure 2: Trends in commonly used marketing elements (2013-2024)

To address the next two research questions, a heatmap was created showing the co-occurrence of Marketing Elements, Research Methodology, and AI Algorithms for 2024 (Figure 3).

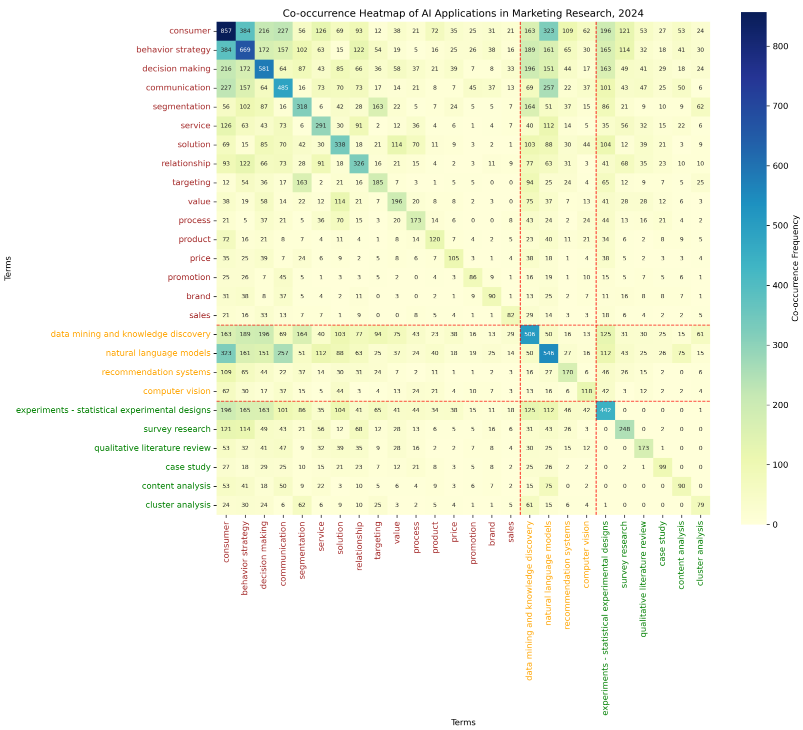

Figure 3: Co-occurrence in 2024.

This heatmap serves as a representative sample of the broader patterns identified in the study. The co-occurrence heatmap for 2024 provides insights into the evolving relationships among marketing elements, methodologies, and AI algorithms. **Consumer and behavioral influence** remain central but are more frequently associated with service and value. **Data mining** remains foundational, complemented by **natural language models** and **recommendation**

systems. Emerging applications of **computer vision** and diversified methodologies, including **survey research** and **qualitative literature review**, signal a broader approach to marketing research with AI applications. **Relationship and consumer-focused solutions** show notable increases, while **segmentation** has declined in prominence. These representative charts highlight key trends and relationships but do not encompass the entirety of the analysis conducted in the study.

4 Summary

This paper employs a Knowledge Discovery in Databases (KDD) framework to analyze the application of AI in marketing. The methodology leverages Large Language Models (LLMs) to automate the screening and analysis of over 300,000 academic papers, reducing the dataset to 9,000 relevant studies. Advanced filtering techniques, including dual-model validation and decision trees, ensure high specificity and sensitivity during data extraction. The study demonstrates how LLMs can be utilized for large-scale literature reviews, enabling the identification of key trends in marketing elements, methodologies, and AI domains, while offering a replicable approach for future research in dynamic fields.

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