

Article

Artificial Intelligence in Digital Marketing: Insights from a Comprehensive Review

Christos Ziakis ^{1,*}  and Maro Vlachopoulou ² ¹ Department of Economics, International Hellenic University, 621 24 Serres, Greece² Information Systems & e-Business (ISEB) Laboratory, Department of Applied Informatics, University of Macedonia, 546 36 Thessaloniki, Greece; mavla@uom.edu.gr

* Correspondence: ziakis@ihu.gr

Abstract: Artificial intelligence (AI) has rapidly emerged as a transformative force in multiple sectors, with digital marketing being a prominent beneficiary. As AI technologies continue to advance, their potential to reshape the digital marketing landscape becomes ever more apparent, leading to profound implications for businesses and their digital outreach strategies. This research seeks to answer the pivotal question: “How could AI applications be leveraged to optimize digital marketing strategies”? Drawing from a systematic literature review guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, this study has identified 211 pertinent articles. Through a comprehensive bibliometric analysis, the findings were categorized into distinct clusters, namely: AI/ML (Machine Learning) Algorithms, Social Media, Consumer Behavior, E-Commerce, Digital Advertising, Budget Optimization, and Competitive Strategies. Each cluster offers insights into how AI applications can be harnessed to augment digital marketing efforts. The conclusion synthesizes key findings and suggests avenues for future exploration in this dynamic intersection of AI and digital marketing. This research contributes to the field by providing a comprehensive bibliometric analysis of AI in digital marketing, identifying key trends, challenges, and future directions. Our systematic approach offers valuable insights for businesses and researchers alike, enhancing the understanding of AI’s evolving role in digital marketing strategies.

Keywords: artificial intelligence; digital marketing; AI-driven marketing

Citation: Ziakis, C.; Vlachopoulou, M. Artificial Intelligence in Digital Marketing: Insights from a Comprehensive Review. *Information* **2023**, *14*, 664. <https://doi.org/10.3390/info14120664>

Academic Editor: Kurt Maly

Received: 10 November 2023

Revised: 12 December 2023

Accepted: 15 December 2023

Published: 17 December 2023



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1. Introduction

The rapid advancement of artificial intelligence (AI) has ushered in a new era for various sectors, particularly in the domain of marketing [1]. As AI technologies evolve, they are equipped with the ability to analyze vast datasets, recognize patterns, make predictions, and even make decisions with minimal human intervention. Digital marketing, characterized by its dynamic nature and reliance on real-time data, stands to benefit immensely from the potential that AI offers. From predictive analytics to personalized user experiences, AI can revolutionize how businesses interact with their audience in the digital space. This symbiosis raises an imperative question, which forms the nucleus of this research: “How could AI applications be leveraged to optimize digital marketing strategies”?

However, the relationship between AI and marketing has been the subject of numerous studies, and the rapid evolution of both fields necessitates continuous exploration. The incorporation of artificial intelligence (AI) in marketing has significantly disrupted and reshaped enterprise operations, marking a new wave of innovation and growth in business strategies. Chintalapati and Pandey thoroughly explored the role and impact of AI in contemporary marketing, emphasizing its transformative potential [2]. In their systematic literature review, they identified five core functional themes in marketing where AI has been prominently deployed: integrated digital marketing, content marketing, experiential marketing, marketing operations, and market research. Their study has analyzed a total

of 170 use cases from the existing literature, shedding light on the myriad of ways in which AI has been harnessed to enhance the overall quality and efficiency of marketing outcomes. On a similar note, Verma et al. recognized the transformative potential of disruptive technologies, especially AI, in redefining business paradigms. Focusing on AI's role in marketing, their research endeavored to offer a comprehensive overview of the subject spanning almost four decades, from 1982 to 2020 [3]. Through the systematic review of a staggering 1,580 papers, Verma and colleagues sought to identify the most influential authors and sources that have been pivotal in shaping the discourse around AI in marketing.

However, although the relationship between AI and marketing has been the subject of the above studies, the rapid evolution of both fields necessitates continuous exploration. Rapid advancements in AI technology, particularly the introduction of generative AI tools like ChatGPT and Google Bard, alongside the evolving dynamics of digital marketing, highlight the need to continually update our grasp of their pivotal interplay, especially in the realm of digital marketing strategies. Such a holistic examination is pivotal for practitioners and scholars alike to grasp the full breadth of the opportunities that AI presents in this domain.

This research endeavors to contribute to the field by systematically analyzing the intersection of AI and digital marketing and revealing emerging patterns. Our findings offer a novel perspective on how AI can be leveraged to optimize digital marketing strategies.

The subsequent sections are structured to provide a thorough exploration of the topic. We begin with the methodology, detailing our systematic literature review approach guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework [4]. This is followed by a bibliometric analysis, offering a quantitative assessment of the existing literature. We then delve into clustering, categorizing the findings into distinct themes for easier comprehension. Each cluster is then meticulously reviewed to provide insights into its relevance and applications in digital marketing. Finally, the conclusion wraps up the key findings, paving the way for recommendations on further research.

2. Materials and Methods

For this systematic literature review on the interplay between AI and marketing, we employed the PRISMA framework. An exhaustive search was conducted on the Scopus database in July 2023, targeting the TITLE-ABS-KEY fields with the combined keywords "Artificial Intelligence" AND "Marketing". This initial search yielded 3327 results. To ensure relevance and manageability, we applied specific filters: only scientific journal articles written in English were considered, and we restricted our search to the publication years spanning January 2015–July 2023. This refined our pool to 849 articles.

In our exploration of the synergies between AI and digital marketing, a strategic decision was made during the initial stages of our systematic literature review. Recognizing the expansive realms of both AI and marketing, we opted to employ a broad-based keyword strategy by searching for "Artificial Intelligence" AND "Marketing" in the Scopus database. This approach was deliberately chosen to cast a comprehensive net, ensuring we did not inadvertently overlook relevant studies that might be tangentially labeled. However, to maintain the focus on our core area of interest—digital marketing—a meticulous screening phase followed. During this phase, records not explicitly related to digital marketing were judiciously excluded. This method of beginning with a broader search and subsequently narrowing it down ensured both the breadth and depth of our research scope, capturing a holistic picture of the intersection of AI and digital marketing in the literature.

The screening based on titles and abstracts whittled this down to 310 articles, and 26 articles could not be retrieved. Upon further scrutiny for eligibility criteria, we arrived at a final count of 211 articles that formed the core of this review. Figure 1 depicts the PRISMA framework flowchart.

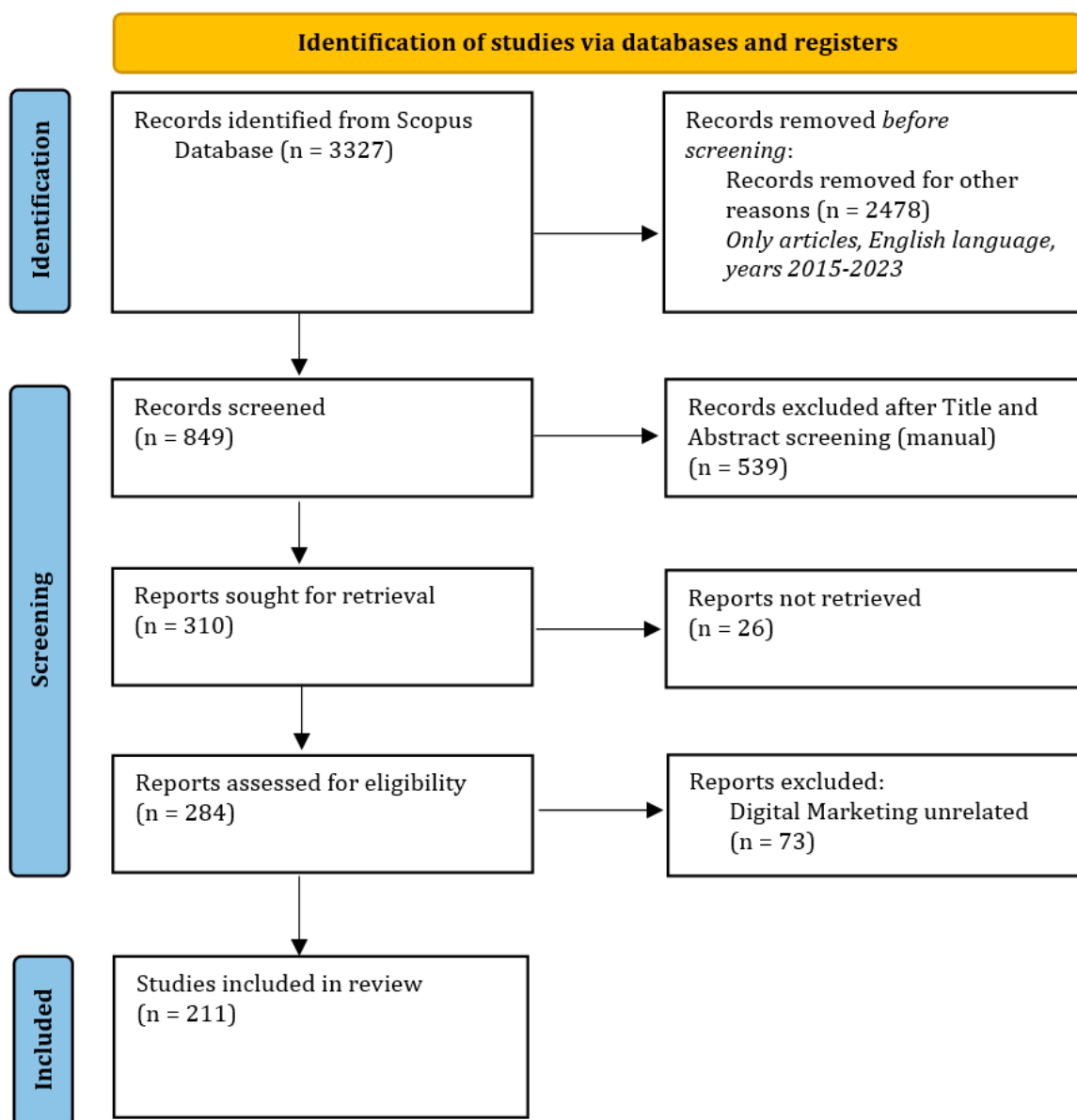


Figure 1. PRISMA framework flowchart.

In the subsequent phase of our systematic literature review, we leveraged R Studio, a powerful tool for statistical computing and graphics, coupled with the Biblioshiny package, to delve deeper into the data analysis [5]. Biblioshiny, an interactive web interface for bibliometric analysis, was instrumental in streamlining our exploration of the collected research articles. Through this combination, we were able to efficiently visualize, categorize, and interpret publication trends, authorship patterns, citation networks, and thematic concentrations in the domain of AI and marketing. This computational approach ensured a meticulous and data-driven analysis, allowing for a comprehensive understanding of the landscape of the literature on our topic.

This literature review extends from January 2015 to July 2023, encompassing a period of eight years. Over this period, 134 sources were employed, consisting of journals, books, and other materials. A total of 211 documents were examined, indicating a robust annual growth rate of 42.5%. These documents, on average, were about 1.83 years old, and each had received approximately 23.85 citations. In total, 12,691 references were consulted in the course of this research.

From the analyzed documents, 681 unique keywords (ID) were identified, and the authors of the papers used 714 unique keywords (DE) in their work. This review included the work of 667 different authors, 26 of whom had written their papers individually. In terms of author collaboration, there were 26 single-authored papers. Each document, on average, was co-authored by approximately 3.49 authors. The data also showed a high degree of international collaboration, with 32.7% of the papers involving authors from different countries. This information is summarized in Table 1.

Table 1. General information about records extracted.

Description	Results
Main information about data	
Timespan	2015:2023
Sources (journals, books, etc.)	134
Documents	211
Annual growth rate %	42.5
Document average age	1.83
Average citations per doc	23.85
References	12,691
Document contents	
Keywords plus (ID)	681
Author's keywords (DE)	714
AUTHORS	
Authors	667
Authors of single-authored docs	26
Authors collaboration	
Single-authored docs	26
Co-authors per doc	3.49
International co-authorships %	32.7
Document types	
Article	211

3. Results

3.1. Descriptive and Scientometric Analysis of Records

Figure 2 showcases the evolution of scientific production on the topic of AI and marketing from 2015 to 2023. In the initial years, from 2015 to 2017, the topic appeared to be in its infancy, with a modest output of only three to four articles annually. This suggests that during this period, the topic might have been emerging or not yet widely recognized in the scientific community. However, by 2018, there was a discernible growth in interest, as evidenced by the more than doubling of articles to ten. This momentum continued into 2019 with 17 articles, indicating a steady rise in research interest and contributions. The year 2020 witnessed a further increment to 21 articles, maintaining the trend. Then, 2021 marked a significant surge in publications, with 34 articles, suggesting that the topic might have gained substantial traction or some breakthroughs spurred more research. This uptick became even more pronounced in 2022, with a record of 68 articles, doubling the previous year's count.

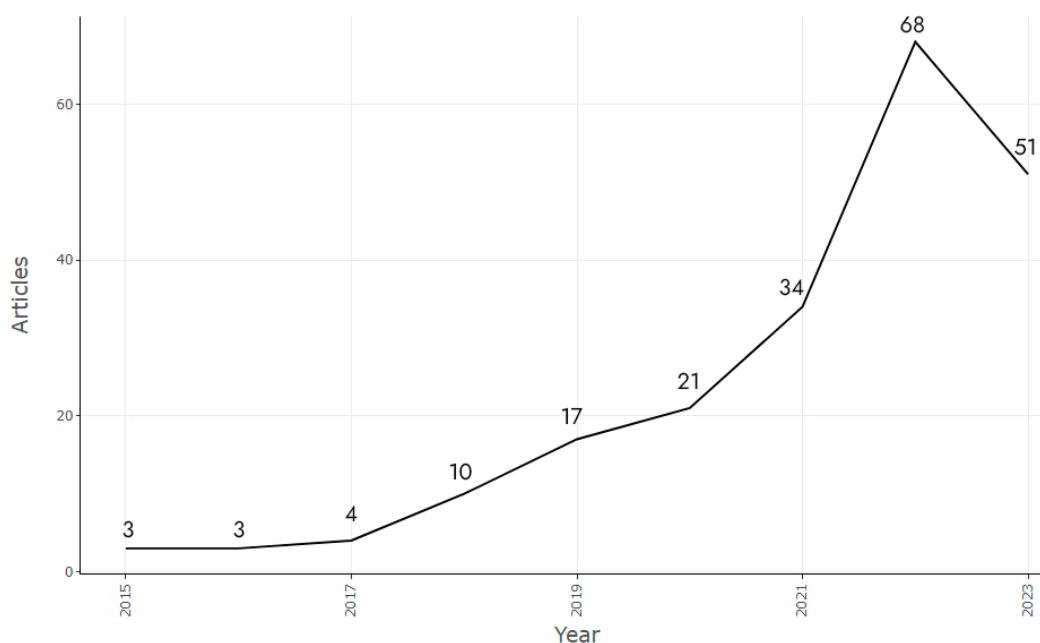


Figure 2. Allocation of the published literature: yearly research publication/growth until July 2023.

In summary, over these nine years, the topic has transitioned from a niche area of interest to a prominent field of study, experiencing peaks and troughs in its scientific production.

3.1.1. Most Frequent Sources

Table 2 presents the leading journals in terms of article publication count, as determined by the bibliometric analysis. To maintain brevity and focus on the most prolific sources, only the top 18 journals are included in this table. The complete analysis encompasses a total of 134 sources. Among these, a distribution pattern emerges: three journals have each published five articles, eleven journals have published three articles each, fifteen journals have contributed two articles each, and one hundred and one journals have published one article each.

3.1.2. Bradford's Law

Figure 3 illustrates the distribution of articles across journals based on Bradford's Law using the Biblioshiny library. It represents the "Core Sources" within the field of AI in digital marketing as determined by our bibliometric analysis. Core Sources are identified based on their centrality to the research area, measured by the number of citations or the frequency of appearances across the corpus of analyzed literature. The journals and publications highlighted in the shaded area are those that have been most frequently cited or referenced within our dataset, indicating their pivotal role in the development and dissemination of knowledge in this domain.

As shown in Table 3, zone 1 includes the most prolific journals, with a total of 15 journals accounting for 71 articles. The "Journal of Business Research" leads this zone, having published 10 articles. This zone highlights journals that consistently publish on the topic and are likely the core sources for researchers in the field. Zone 2 encompasses the next 50 journals, cumulating to 71 articles. Each of these journals has published between one and two articles on the topic. This zone represents a broader range of journals that sporadically delve into the subject matter but are not primarily focused on it. Finally, Zone 3 comprises the broadest range of journals, with 69 journals each contributing around one article, totaling 69 articles. These journals may have ventured into the topic occasionally but do not regularly cover it. For a comprehensive view of the data, the complete table can be found in Appendix A.

Table 2. Most frequent sources.

Sources	Articles
Journal of Business Research	10
Applied Marketing Analytics	9
Journal of Retailing And Consumer Services	7
Industrial Marketing Management	6
Australasian Marketing Journal	5
Journal of The Academy of Marketing Science	5
Psychology And Marketing	5
European Journal of Marketing	3
IEEE Access	3
International Journal of Information Management	3
International Journal of Research In Marketing	3
Journal of Brand Strategy	3
Journal of Interactive Marketing	3
Journal of Product And Brand Management	3
Journal of Research In Interactive Marketing	3
Mobile Information Systems	3
Sustainability	3
Technological Forecasting And Social Change	3

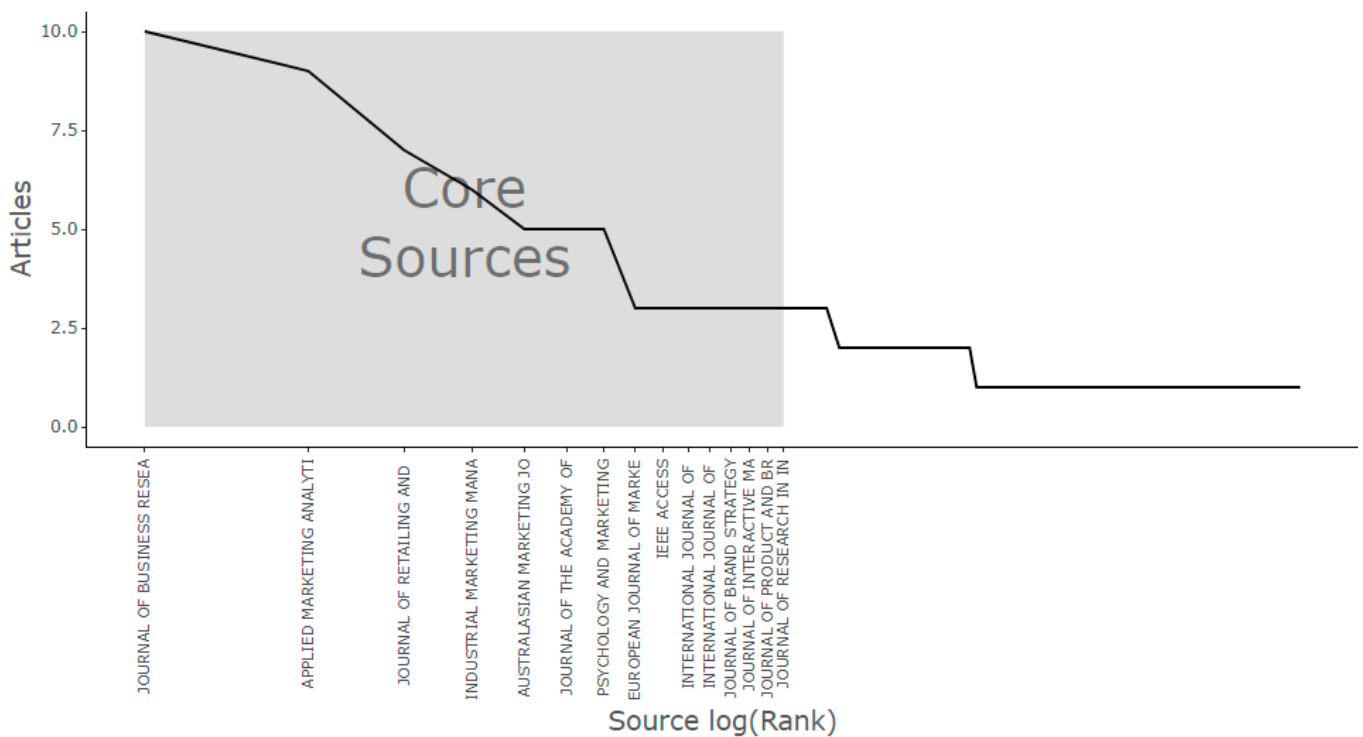


Figure 3. Source clustering through Bradford’s law.

Table 3. Zone-wise distribution of journals.

Zone	Journals	Articles	% Journals	% Articles	Multiplier
Zone 1	15	71	11.19%	33.65%	-
Zone 2	50	71	37.31%	33.65%	3.33
Zone 3	69	69	51.49%	32.70%	1.38
Total	134	211	100.00%	100.00%	2.36

According to the accuracy computation, the observed data are quite close to the distribution predicted by Bradford’s Law:

$$\begin{aligned}
 &1 : n : n^2 ; \\
 &15 : 50 : 69 ; \\
 &15 : 15 \times 2.36 : 15 \times (2.36)^2 \quad :: \quad 1 : n : n^2; \\
 &15 : 35.40 : 83.54 > 133.94; \\
 &\% \text{ error} = (133.94 - 134) / 134 \times 100; \\
 &\% \text{ error} = -0.04 .
 \end{aligned}
 \tag{1}$$

3.1.3. Lotka’s Law

In Figure 4, we present the distribution of publications in our domain of study as per Lotka’s Law, a key bibliometric measure. Lotka’s Law posits that the number of authors producing a certain number of publications in a specific field follows an inverse square law distribution. This means that a small number of authors tend to produce a large portion of the work, while the majority contribute fewer publications.

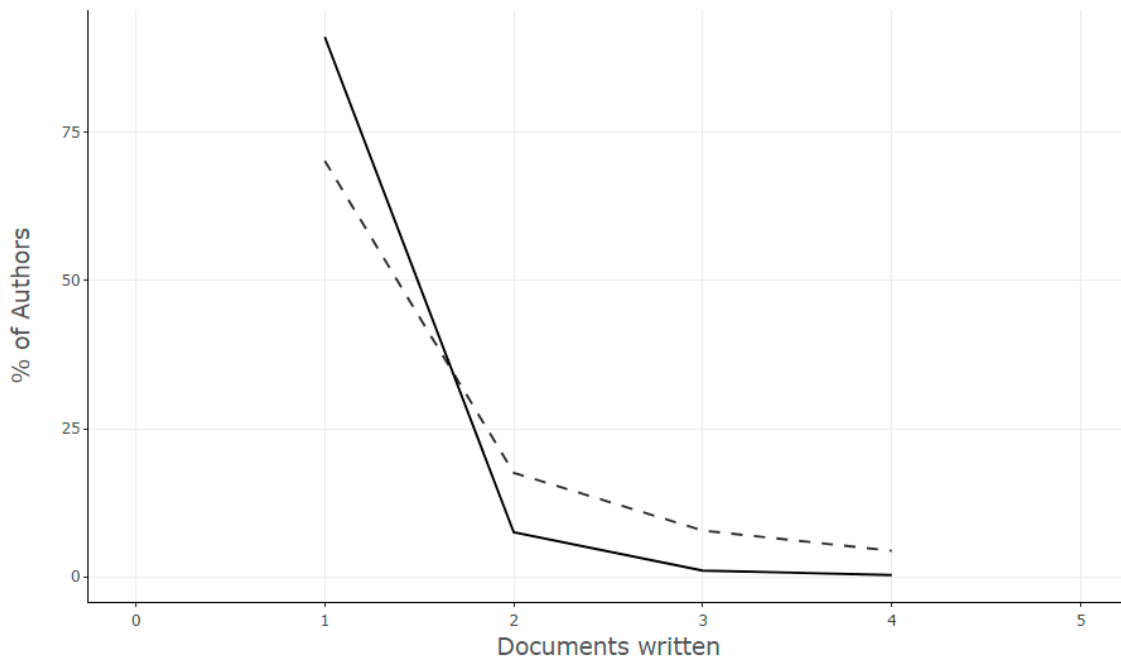


Figure 4. Lotka’s Law. The solid line represents the actual distribution of publications in the dataset. The dotted line represents the theoretical distribution predicted by Lotka’s Law.

The formula for Lotka’s Law is as follows:

$$X^n Y = C \tag{2}$$

In Table 4, we observe the actual distribution of authorship in our dataset. The majority of the authors, precisely 608 or 91.2% of them, have written only one publication. A smaller

group of 50 authors, representing 7.5% of the total, have written two publications. An even smaller group of seven authors, which is 1% of the total, have contributed three publications each. Lastly, a very select group of two authors, making up 0.3% of the total, have written four publications. This distribution illustrates the principle of Lotka's law, where a large number of authors produce a single work, and as the number of works increases, the number of authors capable of producing that many works decreases, typically in an inverse square proportion.

Table 4. Calculations for the Lotka's law.

Publication (X)	No. of Authors (Y)	The Proportion of Authors
1	608	0.912
2	50	0.075
3	7	0.01
4	2	0.003

The data from our study exhibit a general adherence to Lotka's Law, with a majority of authors contributing a single publication and a decreasing number of authors contributing multiple publications. However, there are noticeable deviations from the expected inverse square law distribution. Specifically, the proportion of single-publication authors is higher than what Lotka's Law might predict, and there are variations in the numbers of authors with two to four publications. These deviations could be indicative of the unique dynamics in the field of AI and digital marketing, such as its welcoming nature toward new researchers, its interdisciplinary approach, and the rapid development of new topics, leading to a wide array of authors each focusing on specific niche areas.

3.1.4. The Most Relevant Countries by Corresponding Authors

Concerning corresponding authors' countries and their active involvement in research on the AI and digital marketing subject, China leads with a total of 34 articles, comprising 25 single-country publications (SCP) and 9 multi-country publications (MCP), with the highest frequency of 0.161, as indicated in Table 5 and Figure 5. The United States follows with 25 articles, of which 21 are SCP and 4 are MCP, showcasing a frequency of 0.118. Alongside these countries, India, the United Kingdom, and Australia are significant contributors to the research on AI and digital marketing, although their MCP ratios vary, reflecting different levels of international collaboration. Notably, the United Kingdom has a higher ratio of MCP to SCP, suggesting a strong inclination towards international collaboration in their research approach.

3.2. Literature Clustering

The advancement of research in the interdisciplinary fields of AI and digital marketing has given rise to key thematic clusters. The bibliometric analysis, which delves into the quantitative analysis of publications to discern patterns and trends, has proposed several significant themes that shape the landscape of current research in this domain. Let's explore these thematic evolutions more closely.

The clustering of our dataset was conducted using the biblioshiny application, a graphical interface for the Bibliometrix R package designed specifically for bibliometric analysis. To ensure the integrity and specificity of our clusters, we implemented a systematic approach to refine the dataset and the clustering parameters. Before clustering, we performed a crucial preprocessing step where synonyms were meticulously identified and excluded to maintain the distinctiveness of each category. This step was essential to prevent the conflation of conceptually similar but distinct terms, thereby enhancing the accuracy and relevance of the resulting clusters.

Table 5. Corresponding authors' countries.

Country	Articles	Single-Country Publication	Multi-Country Publication	Frequency	Multi-Country Publication Ratio
China	34	25	9	0.161	0.265
USA	25	21	4	0.118	0.16
India	15	13	2	0.071	0.133
UK	11	4	7	0.052	0.636
Australia	6	3	3	0.028	0.5
Hong Kong	5	2	3	0.024	0.6
Korea	5	4	1	0.024	0.2
UAE	5	4	1	0.024	0.2
Finland	4	1	3	0.019	0.75
France	4	0	4	0.019	1
Portugal	4	4	0	0.019	0
Canada	3	0	3	0.014	1
Germany	3	3	0	0.014	0
Greece	3	3	0	0.014	0
Italy	3	2	1	0.014	0.333
Mexico	3	1	2	0.014	0.667
Netherlands	3	1	2	0.014	0.667
Spain	3	2	1	0.014	0.333
Switzerland	3	2	1	0.014	0.333

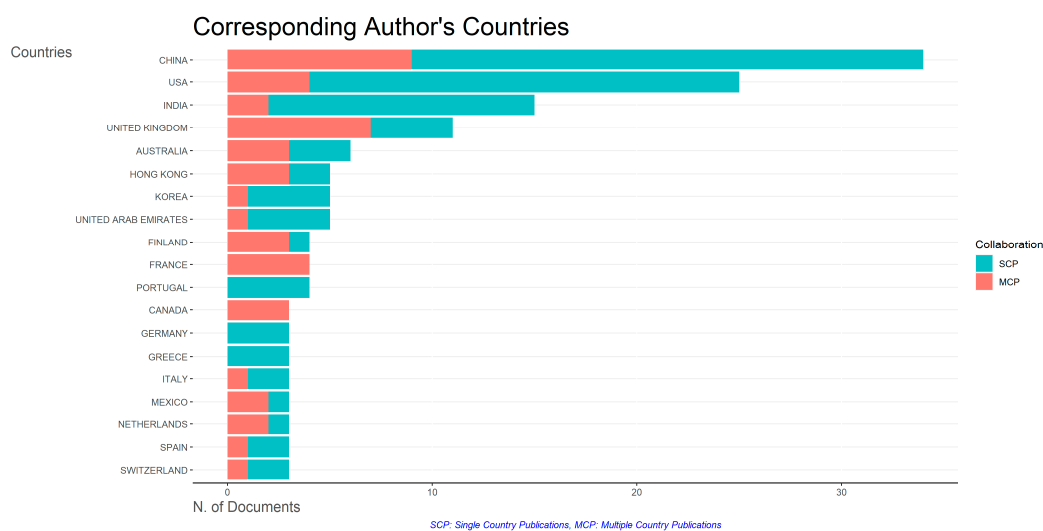


Figure 5. Countries of corresponding authors represent collaboration between different countries (multi-country publications, MCP) and collaboration within the same country (single-country publications, SCP).

In our analysis, we selected specific parameters to guide the clustering process. We set the minimum cluster frequency at nine, which determined the smallest group size that we considered, focusing our analysis on the most significant and recurring themes. The community repulsion was set at zero, affecting the formation of groups in our analysis where a lower value leads to broader, more inclusive groups. For the clustering algorithm, we used the Walktrap algorithm. The application of these parameters was facilitated through the automated clustering capabilities of biblioshiny, which leverages advanced algorithms to categorize the data effectively. The chosen combination of minimum cluster frequency, community repulsion, and the Walktrap algorithm was instrumental in achieving a balance between cluster granularity and comprehensiveness, thus enabling us to extract meaningful patterns and themes from the dataset.

Figure 6 illustrates the thematic mapping of key research areas, where the size of the bubbles represents the frequency of occurrence for each theme within the dataset, and their placement along the axes reflects their centrality and density, indicating their relevance and development within the field. The process involves an algorithmic analysis of bibliometric data to cluster related terms based on co-occurrence and then mapping them according to their calculated centrality (relevance degree) and density (development degree). Each label corresponds to a clustered theme derived from the literature, providing a visual representation of the thematic structure and evolution in the domain of artificial intelligence in digital marketing.

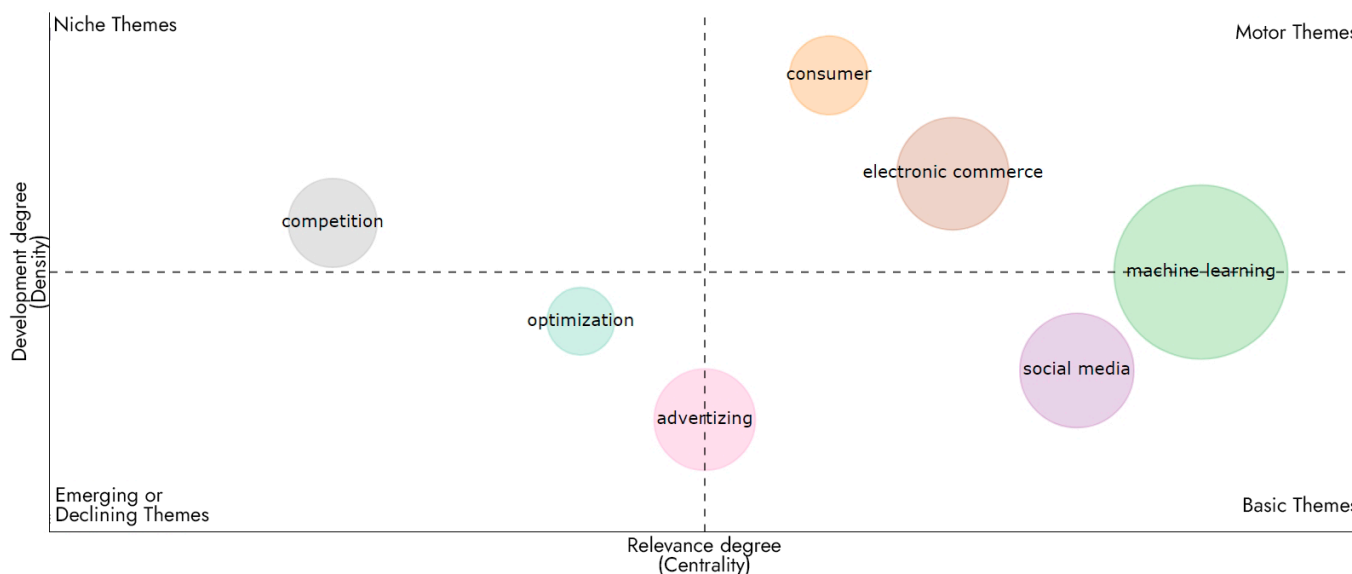


Figure 6. Thematic Evolution.

In the intricate realm of AI and digital marketing, several dominant themes have emerged, shaping the landscape of research and application. The most central theme, both in terms of its centrality (6.935962368) and frequency (223), is AI/ML algorithms. This suggests a significant focus on the tools and techniques of AI as the bedrock of modern digital marketing. The density of the research in this area (70.96509298) further signifies that the works in this cluster are closely interconnected, emphasizing the interdependent nature of AI techniques.

Another pivotal theme is social media. While its centrality stands at 3.151262626, it holds substantial importance with a frequency count of 32. The theme underscores the undeniable influence of social platforms in today’s digital marketing strategies. Similarly, e-commerce has a balanced role in the domain, mirrored by its centrality of 3.131944444 and a frequency of 32, illustrating the growing relationship between AI and online retail strategies.

The intricate understanding of consumer behavior through AI has become densely connected, as indicated by its high density value of 105. Even though it is not the most central theme, with a centrality value of 1.5, the research in this domain is highly interconnected, and with a frequency of 10, it remains an essential study area.

Digital advertising and optimization also carves out a significant niche. Its centrality might be 1.048611111, but with a frequency of 34, it slightly surpasses ‘Social Media’ and ‘E-Commerce’, showcasing the importance of AI in refining and enhancing digital advertising strategies. The “budget optimization” cluster has a Callon centrality of 1, a Callon density of 63.89, ranks fourth in both centrality and density, and appears seven times in the dataset.

Lastly, competitive strategies in the age of AI, though not as central with a value of 0.395833333, has a commendable density of 72.91666667. With a frequency of 14, it is evident that harnessing AI to understand and devise competitive strategies in digital marketing

remains an intriguing and valuable area of study. This information is summarized in Table 6.

Table 6. Thematic evolution.

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
AI/ML Algorithms	6.935962368	70.96509298	9	5	223
Social media	3.151262626	58.77525253	8	3	32
Consumer Behavior	1.5	105	6	9	10
E-Commerce	3.131944444	78.90946502	7	7	32
Digital Advertising	1.048611111	54.05092593	5	2	34
Budget Optimization	1	63.88888889	4	4	7
Competitive Strategies	0.395833333	72.91666667	2	6	14

Cluster-Based Literature Table

In the following sections, Tables 7–13 present a detailed analysis of key nodes within our bibliometric network, derived from the Biblioshiny library. These tables are instrumental in identifying and understanding the most influential elements within the network of the literature on artificial intelligence in digital marketing. The analysis employs three pivotal centrality measures, each offering unique insights into the positioning and influence of nodes (such as authors, papers, or terms) within the network. Betweenness centrality (Btw centrality) reflects the extent to which a node acts as a bridge within the network. Nodes with high betweenness centrality often connect different clusters or groups, indicating their role in facilitating information flow and integrating diverse ideas or fields. Closeness centrality (Clos centrality) indicates how close a node is to all other nodes in the network based on the shortest paths. Nodes with high closeness centrality are typically well positioned to quickly disseminate or gather information, signifying a central role in the network’s communication dynamics. PageRank centrality assigns importance to nodes based on their connections. A node with high PageRank centrality is not just well connected but is also linked to other highly connected or important nodes, highlighting its influence and prominence in the literature.

Tables 7–13 utilize these centrality measures to provide a comprehensive understanding of the structure and influence within the scholarly network, revealing pivotal elements that shape the field of AI in digital marketing.

For the cluster of AI/ML algorithms, the data suggest a strong focus on foundational technologies such as machine learning, which is leading the discussion within the field. The high frequency and centrality of terms like commerce and sales imply a significant interest in applying AI to solve complex problems in the business sector. The presence of consumer behavior and decision-making-related keywords indicates that understanding and predicting user actions is also a vital area within AI applications. Technical aspects like big data and data mining, though not as frequently mentioned, are critical to AI development, likely due to their role in training and improving AI models.

In the social media cluster, social media itself is the leading topic, showing its prominence in digital marketing discussions. The centrality of keywords like social media marketing and information management reflects the importance of managing and analyzing the vast amount of data generated through these platforms. Intelligent systems and online systems also indicate a trend toward automation and the use of AI to manage social media activities.

Table 7. AI/ML algorithms cluster.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
machine learning	64	1055.820511	0.006024096	0.121646468
commerce	34	768.4475448	0.005882353	0.070993813
sales	16	198.3310565	0.005025126	0.037507544
consumer behavior	14	236.1942357	0.005025126	0.023596581
decision making	10	249.171953	0.005235602	0.024742808
big data	8	187.7675854	0.005208333	0.022524782
data mining	6	210.0452139	0.005263158	0.018984255
decision support systems	6	76.34349747	0.004926108	0.015931389
forecasting	6	66.51589138	0.004672897	0.015440563
marketing strategy	6	57.67243825	0.004807692	0.014109938
strategic planning	6	72.06109004	0.004901961	0.014914574
customer satisfaction	4	44.00446478	0.004694836	0.010154666
information analysis	4	49.51062728	0.00462963	0.011547683
data handling	3	10.37739132	0.004273504	0.00761223
marketing models	3	24.11344078	0.004672897	0.009468987
potential customers	3	31.80981655	0.004524887	0.010737864
precision marketing	3	22.86960343	0.004291845	0.010150383
sentiment analysis	3	37.8349971	0.004926108	0.008634345
AI technologies	2	11.29912198	0.004651163	0.005357946
customer profiles	2	3.328993004	0.004032258	0.004901569
customer segmentation	2	13.33416055	0.004219409	0.00555014
decision trees	2	10.94361999	0.004166667	0.007045056
digital technologies	2	22.21773731	0.004926108	0.006665199
knowledge management	2	32.56890359	0.005025126	0.008251596
marketing efficiencies	2	9.040698082	0.004347826	0.005394081
marketing operations	2	10.8076371	0.004784689	0.006175678
online reviews	2	13.24157758	0.004219409	0.005098014
product and services	2	26.74020362	0.004950495	0.008448213
product planning	2	12.00061104	0.004273504	0.005502575
risk assessment	2	40.67836531	0.004901961	0.007026794

Table 8. Social media cluster.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
social media	11	200.9024374	0.005050505	0.028361704
social media marketing	5	21.49512311	0.004484305	0.011691877
information management	4	79.79239658	0.005181347	0.009814957
intelligent systems	3	54.22078537	0.005	0.008588241
online systems	3	48.35029125	0.004854369	0.009983508
data analytics	2	6.264163348	0.004273504	0.006918915
managerial implications	2	21.49299009	0.004464286	0.006461095
products and services	2	41.57412184	0.004830918	0.007209013

Table 9. Consumer behavior cluster.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
consumer	2	94.44152168	0.004761905	0.009413763
human	2	106.189656	0.004975124	0.008105341
language processing	2	1.460207337	0.003636364	0.007589943
natural language processing	2	1.460207337	0.003636364	0.007589943
trust	2	5.60828578	0.004081633	0.005832891

Table 10. E-commerce cluster.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
electronic commerce	9	159.2476837	0.005319149	0.022089932
chatbots	3	8.072186379	0.004587156	0.003915811
e-commerce	4	122.6998775	0.005263158	0.013758074
marketing activities	3	67.80234082	0.004484305	0.009957807
purchase intention	3	24.5466894	0.004444444	0.011137783
consumer purchase	2	10.56621641	0.004545455	0.008461717
machine learning approaches	2	26.16709662	0.004651163	0.007037929
natural language processing systems	2	44.71454766	0.004694836	0.004845591
purchasing	2	10.56621641	0.004545455	0.008461717
websites	2	82.79793797	0.004716981	0.005511432

Table 11. Digital advertising cluster.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
advertizing	6	125.0898572	0.005154639	0.016861204
advertising	4	102.1836488	0.004975124	0.013171544
marketing communications	3	16.69280952	0.004405286	0.005786586
reinforcement learning	2	62.72847676	0.005154639	0.006428031
search engines	2	4.541524578	0.004166667	0.005586297
advertising campaign	2	38.74213249	0.004201681	0.005220361
online advertising	2	76.30294395	0.004405286	0.007368908
display advertisings	2	13.36106278	0.003636364	0.007235011

Table 12. Optimization and budget control.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
optimizations	4	64.48512097	0.004672897	0.010836125
optimization	3	66.44964344	0.004255319	0.007581942
budget control	2	8.772481114	0.003389831	0.006525159
click-through rate	2	13.36106278	0.003636364	0.007235011

Table 13. Competitive strategies cluster.

Keyword	Frequencies	Btw Centrality	Clos Centrality	PageRank Centrality
competition	4	58.2277428	0.004504505	0.00980697
classifiers	2	34.1691082	0.004524887	0.005263117
competitive advantage	2	3.89417657	0.004115226	0.005554099
planning	2	7.508933566	0.00390625	0.003154914
profitability	2	14.74597559	0.003968254	0.005656593
sustainable development	2	3.708766234	0.003508772	0.005045295

The consumer behavior cluster has a lower frequency of keywords, suggesting a more niche but still significant interest in how consumers interact with technology. Terms like natural language processing are not frequent but have a presence, indicating the role of AI in understanding and processing human language, which is a growing area of interest.

E-commerce is a robust cluster, with electronic commerce leading in centrality, pointing to its significant role in the digital economy. The presence of keywords like chatbots, marketing activities, and purchase intention demonstrates the diverse applications of AI in

enhancing the shopping experience, from customer service to understanding what drives consumers to buy.

Digital advertising's discussion is centered around the application of AI in advertising, with keywords like advertising and advertizing having the highest centrality, indicating their importance in the industry. Marketing communications and the use of search engines show the integration of AI in reaching and engaging customers more effectively.

In optimization and budget control, the focus is on efficiency and cost-effectiveness, with terms like optimizations and optimization being central. This suggests that there is a significant emphasis on using AI to enhance marketing strategies within budget constraints.

The competitive strategies cluster indicates an emphasis on maintaining and gaining an edge in the market. Keywords like competition, classifiers, and competitive advantage suggest that AI is viewed as a critical tool for businesses to outperform their rivals and to create strategies that ensure long-term sustainability and profitability.

To evaluate the performance of the clusters of our dataset, we utilized three statistical metrics: the Silhouette Score, the Calinski–Harabasz Index, and the Davies–Bouldin Index [6]. The Silhouette Score assesses how well each object lies within its cluster, the Calinski–Harabasz Index evaluates cluster dispersion, and the Davies–Bouldin Index measures the average similarity between clusters.

The Silhouette Score is a measure of how similar an object is to its own cluster compared to other clusters. The score ranges from -1 to $+1$, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters.

The Silhouette Score for a single sample is given by the following:

$$s = \frac{b - a}{\max(a, b)} \quad (3)$$

where:

- a is the mean distance between a sample and all other points in the same class;
- b is the mean distance between a sample and all other points in the next nearest cluster.

The Silhouette Score for the entire dataset is the mean of the Silhouette Score for each sample. Our model received a Silhouette Score of 0.397, which indicates moderate separation between the clusters.

The Calinski–Harabasz Index is the ratio of the sum of between-clusters dispersion and within-cluster dispersion for all clusters where higher values generally indicate a model with better-defined clusters.

The Calinski–Harabasz Index (CHI) is defined as follows:

$$CHI = \frac{Tr(B_k)}{Tr(W_k)} \times \frac{N - k}{k - 1} \quad (4)$$

where:

- B_k is the between-group dispersion matrix and $Tr(B_k)$ its trace;
- W_k is the within-cluster dispersion matrix and $Tr(W_k)$ its trace;
- N is the number of points, and k is the number of clusters.

Our model achieved a Calinski–Harabasz Index of 255.25, indicating a relatively strong cluster structure [7].

The Davies–Bouldin Index measures the average similarity between each cluster and its most similar one, where lower values indicate better clustering.

The Davies–Bouldin Index (DBI) is calculated as follows:

$$DBI = \frac{1}{k} \sum_{i=1}^k \max_{i \neq j} \left(\frac{\sigma_i + \sigma_j}{d(c_i + c_j)} \right); \quad (5)$$

where:

- k is the number of clusters;
- σ_i is the average distance of all points in cluster i to the centroid c_i of cluster i ;
- $d(c_i + c_j)$ is the distance between centroids c_i and c_j .

A value of 0.477 in our model indicates a good level of separation between the clusters, implying that each cluster is distinct from its closest cluster [8].

These metrics collectively suggest that the applied clustering methodology effectively captures the inherent structure of the dataset, providing distinct and meaningful clusters.

4. Discussion

In this research, we initially conducted a bibliometric analysis using a comprehensive set of 211 references to gain a broad understanding of the current landscape of artificial intelligence in digital marketing. However, for a more focused and in-depth discussion in this paper, we chose not to discuss all of these references but rather to focus on those that are most pertinent to our specific research questions. By doing so, we aimed to achieve a balance between depth and breadth, offering detailed insights into the key themes and trends while still providing a representative overview of the wider body of literature.

4.1. AI/ML Algorithms Cluster

Çalı and Balaman introduced a novel system that leverages sentiment analysis and multi-criteria assessment for improved decision making in product ranking [9]. This system captures online customer reviews and uses them to rank products according to customer satisfaction, providing businesses with insights into the preferences of their target audience. Toader et al. delved into the role of AI chatbots, finding that errors and gender biases in chatbot interfaces significantly influence consumer trust. Their study revealed that female virtual assistants tend to be forgiven more readily for mistakes compared to their male counterparts [10].

Micu et al. presented a deep learning-based system for on-site customer profiling and hyper-personalization, which can detect and gather real-time data about customers in physical stores, offering insights into customer behavior and preferences [11]. Yang et al. highlighted the importance of AI in precision marketing, emphasizing its role in delivering more targeted and personalized marketing campaigns [12]. Yin and Qiu investigated the impact of AI technology on online shopping, suggesting that AI-driven insights into consumer behavior can significantly enhance online purchase intentions [13].

Martínez et al. developed a predictive analytics tool for forecasting future customer behavior, allowing businesses to better align their sales and marketing strategies with consumer needs [14]. Han et al. provided a comprehensive bibliometric analysis of AI in B2B marketing, categorizing the utilization of AI into five domains and offering both past trends and future directions in the field [15]. Olan et al. emphasized the synergy between AI and consumer knowledge sharing in online communities, suggesting that AI can refine consumer attitudes and behaviors based on shared experiences [16].

Lastly, Sarath Kumar Boddu et al. explored the role of AI, machine learning, and robotics in digital marketing. Their findings underscored the significant influence of AI on marketing operations, suggesting that data-driven strategies can provide businesses with a competitive edge [17].

To summarize, this cluster showcases diverse applications of AI in digital marketing, from sentiment analysis for product ranking to AI chatbots' impact on consumer trust. It also covers systems for on-site customer profiling, predictive analytics for customer behavior, and the role of AI in enhancing marketing operations.

Potential future research directions related to cluster one might include the following:

1. Examination of the long-term impacts of AI and machine learning on consumer trust across diverse cultural contexts.
2. Advanced machine learning techniques for real-time hyper-personalization in both online and physical retail environments.

3. Comparative studies on the effectiveness of different AI algorithms in predictive analytics for various marketing domains.

4.2. Social Media Cluster

Recent advancements in artificial intelligence (AI) have presented innovative approaches to understanding online consumer behavior, particularly in the realm of social media marketing.

Villegas-Ch et al. explored the vast data reservoirs within social media platforms to deduce users' personalities [18]. Through a comprehensive application of artificial intelligence and sentiment analysis on Twitter data, they formulated a machine learning model capable of predicting a user's personality based on their activity. Their findings were particularly promising, demonstrating that with the right approach, social media data harbors invaluable information. Beyond mere personal insights, the potential applications span from devising marketing campaigns to refining recruitment processes.

Aguilar and Garcia delved into the intricate realm of social media advertising, specifically on Facebook. Recognizing the challenges that companies face in optimizing their advertising campaigns, they developed an intelligent system grounded in data mining techniques. Their system not only facilitates the production of ads but is also adaptive, enabling automatic adjustments to enhance ad performance. Such advancements aim to address issues like excessive costs, extensive design hours, and complications in ad creation, ensuring more effective advertisement delivery on platforms as massive as Facebook [19].

Argan et al. undertook a qualitative exploration into social media users' perceptions of AI-infused advertisements [20]. Their methodical approach, comprising semi-structured interviews, unveiled a triad of process themes—'reception', 'diving', and 'break-point'—that captures the users' journey from initial interaction to decision-making regarding AI advertisements. Their research serves as a reservoir of insights for a spectrum of professionals, from content creators to AI researchers, seeking to fathom the nuanced relationship between social media users and AI-driven ads.

Cutler and Culotta discussed the relatively untapped potential of machine learning models in harnessing social media data for marketing research [21]. They spotlighted the challenges in procuring labeled training data and presented innovative weak supervision methodologies as a solution. By leveraging the intrinsic structure of social media, these methods—focusing on training on exemplars and groups—bypass the need for curated data labels, sometimes requiring just a single keyword to kickstart the process.

Perakakis et al. underscored the transformative potential of AI in refining social media monitoring tools. Their research introduced an AI-infused platform designed to provide digital marketers with unparalleled insights [22]. This platform aims to empower brands with effective online reputation management, competitor monitoring, and strategies to enhance their web and social media presence.

Basri investigated the ramifications of AI-assisted social media marketing (AISMM) on the performance of small and medium enterprises (SMEs) in the Saudi Arabian milieu [23]. Through a methodical survey approach, Basri discovered a positive correlation between AISMM and the growth of customer bases for SMEs, culminating in increased profitability. This study delineates the mediating role of effective business management in bolstering the performance of SMEs, highlighting the transformative power of AISMM in enhancing business operations.

Tzafilkou et al. proposed a novel method of predicting purchase intent by analyzing the facially expressed emotions of consumers while viewing social media campaigns. Their multi-stage experiment using FaceReader Online™ involved a range of classification models [24]. Notably, neural networks (NNs) demonstrated a high accuracy rate of 90–91% in predicting consumers' purchase intentions, while random forest (RF) also showed commendable performance at 75%. In contrast, Arasu et al. focused on harnessing machine learning tools to enhance social media marketing strategies. They found that the Waikato

Environment for Knowledge Analysis (WEKA) outperformed other data mining techniques in precision, recall, and F-measure [25].

Similarly, Nuanmeesri et al. sought to analyze patterns and behaviors of social media users, aiming to determine the likelihood of these users becoming customers [26]. Their findings showed that a model combining Multi-Layer Perceptron Neural Network and Correlation-based Feature Selection yielded the highest performance, achieving an accuracy rate of 89.80%. In another study, Salminen et al. explored the potential of machine learning in detecting customers' pain points from user-generated content on social media [27]. Their research concluded that neural networks were most effective, with an accuracy rate of 85% for pain point detection.

The changing landscape of consumer behavior, propelled by the internet and social media, has been captured comprehensively by Dwivedi et al. They highlighted the opportunities and challenges presented by social and digital marketing, emphasizing the transformative role of AI, augmented reality, and other digital tools [28]. Liu-Thompkins et al. posited the concept of "artificial empathy" to improve AI's affective and social customer experiences, advocating its integration into AI marketing applications [29].

Furthermore, Capatina et al. identified the growing prominence of AI in social media marketing, emphasizing the need to align the capabilities of future AI-based software with user expectations [30]. Their research explored the potential of an upcoming AI-based software and its distinctive capabilities in audience, image, and sentiment analysis, which would influence users' intentions to adopt the technology.

Studies in this cluster highlight AI's role in understanding consumer behavior on social media, with applications ranging from personality prediction using Twitter data to AI-assisted social media marketing improving SME performance. The effectiveness of AI in social media monitoring tools and the challenges and opportunities of AI in social media marketing are also discussed. In conclusion, the aforementioned studies underscore the transformative potential of AI in refining social media marketing strategies, offering unique insights into consumer behavior and enhancing the overall online shopping experience.

To advance the knowledge of cluster two, future research directions might include the following:

1. Examination of the evolving role of AI in managing and interpreting complex social media data for personalized marketing.
2. Analysis of the effectiveness of AI-driven advertisements on different social media platforms and their impact on consumer behavior.
3. Ethical implications and privacy concerns of AI in social media marketing, with a focus on user personality prediction and behavior analysis.

4.3. Consumer Behavior Cluster

The recent surge in digital marketing research has led to intriguing findings surrounding the intersection of artificial intelligence (AI) and consumer behavior. Batta et al. delved into the realm of e-commerce, emphasizing the pivotal role of suppliers and sellers [31]. They underscored the value of seller ratings in influencing buying decisions, akin to product ratings. By analyzing sellers' activities on social media, they unearthed a strong connection between seller engagement on social media platforms and their turnover on e-commerce sites. Interestingly, the study advised sellers to veer more toward communication and interaction, rather than traditional marketing strategies. The longitudinal study further posited that an e-commerce firm's foresight into future seller churn and disengagement could be significantly sharpened by monitoring seller performance on social media.

Huang R. et al. took a different trajectory, focusing on the burgeoning field of virtual agents (VAs) in the retail sector [32]. In an environment where AI in retail and service industries is gaining interest, this study addressed the sparse consumer research on virtual agents (VAs). It delved into how trust shapes consumer relationships with VAs, a unique aspect due to VAs' interactive and non-physical nature. Leveraging the "computers as social actors" framework and an adapted Technology Acceptance Model, the study revealed

that trust in VAs, encompassing competence, integrity, and self-efficacy, enhances their perceived usefulness and enjoyment, thereby encouraging continued use. These insights have significant implications for consumer adoption of VAs and the development of related marketing strategies.

Taking a more technical approach, Gkikas et al. endeavored to bridge the chasm between marketing and computer science [33]. Their research offers a unique decision-making model, amalgamating decision trees and genetic algorithms, to predict consumer behavior across digital and physical shopping arenas. Notably, their model achieved commendable classification accuracies, highlighting specific variables tied to gender, household size, and income, which are pivotal in driving marketing decisions.

On a parallel note, Zhang W. et al. explored the implications of AI-driven word-of-mouth systems [34]. Through a meticulously constructed research model, they discerned consumers' heightened attention to the volume of information as opposed to its quality or intensity. Their findings spotlight the mediating role of risk perception in shaping the influence of AI word-of-mouth on purchasing decisions.

Turning the spotlight on the exponential growth of e-retail catalyzed by increased smartphone penetration, Barykin et al. investigated the adoption of messenger chatbots in conversational commerce [35]. Their research elucidated trust as a paramount factor in influencing customer attitudes towards these AI-driven chatbots. The study underscored the potential of chatbots in facilitating more trustworthy interactions, suggesting an avenue for further exploration in anthropomorphic digital technologies.

Vernuccio et al. probed into brand anthropomorphism, particularly in the context of name-brand voice assistants [36]. The nascent domain of voice-activated AI technologies presents intriguing opportunities for branding. Their exploratory research, conducted in the automotive sector, unveiled a multi-layered strategic framework encompassing drivers, intermediate outcomes, and final results, offering a comprehensive understanding of brand anthropomorphism strategies in this space. Olan et al. presented an overarching perspective on the transformative role of digital technologies in reshaping marketing and consumer behavior [16]. Emphasizing the dynamic learning capabilities of AI, they expounded the significance of consumer knowledge sharing in digital communities. Their research suggested that AI, buttressed by consumer insights derived from knowledge sharing, can foster advancements in consumer attitudes and behaviors, providing invaluable insights into marketing mavens industry-wide.

Adwan and Aladwan focused on the influence of AI in e-commerce businesses, particularly online enterprises, using the Stimulus–Organism–Response (SOR) empirical model [37]. Their study, conducted with 230 participants in Jordan, highlighted that the use of AI, through accuracy, interactive experience, and insight, significantly impacted customers' perceptions of hedonic and utilitarian values during their online shopping endeavors.

In another study, Zhou Li underscored the significance of correctly understanding demand information for inventory management in online retail contexts [38]. The research centered on consumer web searches, postulating that insights from these searches can drive inventory models and ordering strategies. To delve deeper into this connection, Zhou Li proposed an inventory model considering the unique attributes of both consumers and retailers in the online search environment. By analyzing the model with practical examples, the study confirmed that the model's construction met the set expectations.

Adding a different dimension to the discourse, Chen et al. embarked on a journey to enhance the explanatory power of machine learning models in understanding consumer purchase behavior in search advertising [39]. They introduced a random forest model that factored in anchoring effects, which can sometimes bias rational consumer behavior. The results of their approach were twofold. Firstly, the machine learning model they employed, based on the random forest algorithm, emerged as a leading choice for deciphering consumer purchase behaviors, with an F1 score of 0.8586. Secondly, the study identified product information as the most significant attribute shaping consumer purchase behav-

ior, with elements like sales level, display priority, granularity, and price playing pivotal roles. Furthermore, they discovered that consumers' purchase intentions were malleable depending on the anchor point presented to them. Specifically, when confronted with high anchor information related to product quality ratings, consumers were more inclined to purchase, whereas price anchors made them compare similar products, often choosing the most cost-effective option. This research not only offers actionable insights for merchants looking to fine-tune their marketing strategies but also enhances the broader understanding of consumer decision-making in the digital shopping landscape.

This cluster explores AI's impact on consumer behavior in e-commerce, including the role of virtual agents and decision-making models that bridge marketing and computer science. The findings indicate AI's significant influence on various aspects of consumer behavior, from trust in virtual agents to word-of-mouth systems.

Potential future research directions related to cluster three might include the following:

1. The integration of virtual agents in retail and service industries and their impact on consumer relationship building.
2. The effectiveness of decision trees and genetic algorithms in predicting consumer behavior across digital and physical shopping platforms.
3. Analysis of the role of AI in influencing consumer perceptions and decision-making in e-commerce settings.

4.4. E-Commerce Cluster

The world of e-commerce has witnessed groundbreaking shifts with the infusion of artificial intelligence (AI) technologies, particularly in the realm of conversational AI. In 2023, Dwivedi et al. undertook an extensive exploration of ChatGPT, a text-generating AI, discussing its multifaceted applications across diverse industries. Their comprehensive study detailed the promising opportunities that this technology offers, such as enhancing productivity and advancing industries like banking and hospitality. Yet, they also highlighted concerns related to privacy, security, biases, misuse, and misinformation. The discussions ventured into debates on potential regulatory needs for such tools [40].

Parallely, the sphere of chatbots in e-commerce was further examined. Li M. and Wang R. found that chatbots employing informal language styles fostered stronger customer relationships, resulting in continued usage and favorable brand attitude [41]. However, this effect was dampened for individuals without a prior relationship with the brand, emphasizing the role of brand affiliation. In a related vein, Kim and Hur inspected the underpinnings of consumer empathy toward AI chatbots. Their research revealed that personalization and anthropomorphism in AI chatbots augmented perceived warmth and competence, culminating in enhanced user acceptance [42].

Meanwhile, Marjerison et al. tapped into China's online shopping ecosystem, leveraging the Use and Gratification theory to comprehend consumer acceptance of chatbots [43]. Both practical (e.g., conversation authenticity) and hedonic (e.g., enjoyment) factors were influential, but concerns about privacy and technological maturity hindered acceptance. Another 2022 study by Trivedi et al. adopted a machine learning approach to predict online purchase intentions. By optimizing a novel algorithm, they managed to provide valuable insights that help e-commerce platforms tailor user recommendations [44].

Diving into the backend of chatbot technology, Ngai et al. shared a prototype of a knowledge-based chatbot designed for customer service in a women's apparel firm. This system amalgamated multiple emerging technologies, and preliminary results seemed promising, indicating effective service enhancement [45].

Lastly, the unprecedented challenges spurred by the COVID-19 pandemic led Silva and Bonetti to explore digital human interactions within the fashion industry. With an analytical focus on consumer attitudes toward these digital entities, the researchers presented pivotal insights to guide the fashion industry in its digital transformation endeavors, especially given the rapid shift towards e-commerce and the rising demand for sustainable practices [46].

The focus of this cluster is on conversational AI and chatbots in e-commerce. The studies discuss ChatGPT's diverse applications, chatbots' role in fostering customer relationships, and the use of AI for enhancing customer service in specific sectors like fashion.

Possible avenues for future research on cluster four might involve the following:

1. Development of sophisticated AI-driven chatbots for enhancing customer experience in e-commerce.
2. Impact of conversational AI on customer service and sales in industries like banking and hospitality.
3. Challenges and opportunities in implementing AI technologies in e-commerce, particularly in privacy and security aspects.

4.5. Digital Advertising Cluster

Artificial intelligence (AI) has substantially transformed the world of online advertising in various innovative ways. One study by Guerreiro et al. underscored how AI, particularly through smart speakers, has brought forth novel advertising methodologies that facilitate human-like dialogues with consumers [47]. Their research, involving 326 participants, found that consumers' acceptance of ads through these AI devices hinges on the perceived usefulness of the smart assistant and hedonic motivations. However, there is a caveat: the ease of use of these smart speakers becomes less relevant when consumers perceive potential privacy risks.

Moving into a slightly different territory, Guo delves into the realm of voice data mining and its implications for e-commerce advertising [48]. With AI's growth, advertising is no longer solely a product of human creativity and knowledge. Using technologies such as association rule models and neural networks, Guo suggests that online advertisements can evolve beyond simple clicks. They can engage users through multi-sensory interactions, creating a richer and more immersive experience. This strategy necessitates a blend of eloquent speech and content harmony, along with precise and elegant advertising language.

Ethical considerations also play a pivotal role in AI's use in advertising, as Rodgers and Nguyen pointed out [49]. They discussed six algorithmic purchase decision pathways that align with various ethical philosophies, emphasizing the importance of aligning AI advertising strategies with ethical principles. Furthermore, they introduced the "intelligent advertising" concept, mapping out its present status and future trajectory.

Meanwhile, Aljabri and Mohammad addressed a growing concern in online advertising: click fraud [50]. As advertising shifts heavily toward online platforms, with the pay-per-click model being predominant, the threat of malicious actors, both human and bots, artificially inflating click counts is real. Their research uses machine learning models to discern between legitimate human clicks and fraudulent ones. Among all models tested, the random forest algorithm stood out as the most effective.

Schultz et al. critically highlighted the growing dependence on AI in enhancing automated bidding strategies in search engine advertising [51]. Their research showcased concerns over the lack of transparency in AI-powered systems, emphasizing the potential pitfalls and challenges advertisers face, especially when they are uninformed about the data driving these decisions. Alarmingly, their study provided empirical evidence showing that such automation can lead to a long-term decline in advertising performance, particularly during periods of data scarcity. This calls for greater scrutiny and understanding of automated decision-making systems to mitigate risks associated with algorithmic blunders in advertising.

Cutler and Culotta examined the revolutionary capabilities of OpenAI's ChatGPT, suggesting its potential impact on search engine optimization (SEO) strategies [21]. Given the chatbot's advanced natural language processing capabilities, the authors projected a shift in digital marketing dynamics, especially in the domain of search engine functionalities. Microsoft's investment in ChatGPT and its subsequent integration into Bing underlines the potential transformation of search marketing and SEO landscapes.

Sabharwal et al. offered insights into the synergetic relationship between digital advertising and AI and their joint role in refining marketing strategies [52]. Their research illustrated how AI and machine learning are reshaping communication avenues in marketing, emphasizing the pivotal role of AI in sculpting successful digital marketing campaigns. Their findings can serve as a cornerstone for strategists and business managers in understanding the interplay between AI, digital advertising, and marketing strategy formulation.

Shi and Wang shed light on the potential of the genetic algorithm back propagation (GABP) neural network in transforming the advertising sector [53]. Their research revealed that the GABP network can be instrumental in predicting the click-through rate (CTR) of web ads, offering advertisers a precise tool to refine their promotional strategies. The study's results underscore the pressing need for innovation in the traditional advertising sector, especially in the age of AI and digital transformation.

Miralles-Pechuán et al. accentuated the evolution of online advertising, pointing to the increasing dominance of mobile network-based advertising [54]. They proposed a machine learning methodology tailored for small ad networks, underscoring the challenges and opportunities in digital marketing for smaller players in the advertising space.

Lastly, Zhang et al. highlighted an emerging challenge in online advertising—the surge of spam comments [55]. These comments, often masquerading as genuine feedback, have been used by businesses to artificially bolster their online ratings. The authors proposed a novel unsupervised learning model to effectively identify and curtail these advanced spam activities, ensuring the integrity of online reviews.

This cluster details AI's transformation of online advertising, discussing novel advertising methodologies, ethical considerations in AI advertising, and the challenges in marketing due to rising costs and generalizations. The need for transparency and innovation in AI-driven advertising strategies is emphasized.

Potential future research avenues for cluster five might include the following:

1. Examination of the effectiveness of AI in creating and delivering personalized advertisements through emerging channels like smart speakers.
2. Ethical considerations and consumer attitudes toward AI in advertising, particularly in voice and data mining.
3. The role of AI in combating challenges such as click fraud in online advertising.

4.6. Optimization and Budget Control

Advertisers constantly grapple with the challenges of optimizing their bids and controlling budgets while ensuring maximum reach and impact. This context has led researchers to delve deep into devising algorithms and methodologies that harness the power of AI to optimize these processes, ensuring that businesses get the best value for every dollar spent. In this light, several studies have come to the forefront. In a research focused on real-time bidding (RTB) in display advertising, Liu and Yu address the challenges posed when estimating the click-through rate (CTR) of ad impressions [56]. They propose a bid-aware active real-time bidding (BARB) algorithm that sets different bid prices for each ad auction to efficiently train an accurate CTR model without overspending. The effectiveness of this approach is demonstrated through empirical studies on real-world data.

Wang et al. addressed the problem of guaranteed display ad (GDA) allocation by leveraging multi-agent reinforcement learning (MARL) [57]. Their innovative approach aimed to optimize the allocation process in dynamic and large-scale scenarios, emphasizing the need for a more coordinated allocation strategy. The hierarchical MARL (HMARL) method that they proposed demonstrated superior performance in real-world applications, highlighting the potential of AI in enhancing the efficiency of ad allocation processes.

This cluster is centered on AI's role in optimizing bids and controlling advertising budgets. It includes studies on real-time bidding algorithms and multi-agent reinforcement learning for ad allocation, underscoring AI's potential to enhance the efficiency of advertising processes.

Future research directions for cluster six could involve the following:

1. Development of AI algorithms for more efficient real-time bidding and ad allocation in digital advertising.
2. Potential of AI in predictive budget allocation and its impact on marketing campaign performance.
3. Integration of AI in optimizing marketing strategies across various digital platforms.

4.7. Competitive Strategies Cluster

In recent years, a growing body of research has explored the intersection of artificial intelligence (AI) and competitive marketing strategies. Wang analyzed the innovation of e-commerce marketing models in the context of big data and AI [58]. The study found that to innovate e-commerce marketing models, it is crucial to prioritize aspects such as market positioning, business strategy, marketing promotion, and operation management. Market positioning, in particular, was highlighted as a significant innovative element.

Similarly, in West Bengal, India, Giri et al. studied the impact of AI on developing marketing strategies in the organized retail sector [59]. They identified that AI plays a significant role in gathering and analyzing customer data, which is instrumental in devising new marketing strategies.

Another study by Miklosik et al. focused on the adoption of machine learning (ML)-based analytical tools in digital marketing [60]. They pointed out a knowledge gap among marketers about ML and its potential benefits. Despite its immense promise, the adoption and utilization of ML-driven analytical tools in marketing management remain low.

Rosa et al. explored AI adoption in Portuguese companies, emphasizing its application in marketing activities [61]. The findings suggest that while AI adoption can provide a competitive advantage, companies face challenges like high investment costs and potential loss of human connection with customers.

Highlighting a novel approach to market segmentation, Chang and Fan proposed replacing human decisions with AI algorithms for better market targeting [62]. Using various AI algorithms, their study showed that AI can effectively aid enterprises in market targeting.

Stone et al. embarked on a literature review of AI applications in strategic situations [63]. They emphasized the need for research on AI's role in strategic marketing decisions, especially given the competitive nature of these decisions.

Lastly, Bag et al. examined the influence of AI powered by big data on knowledge creation in the B2B context [64]. They found that AI significantly affects customer knowledge creation, user knowledge creation, and external market knowledge creation, all of which play a vital role in rational B2B marketing decision-making and consequently influence firm performance.

This cluster explores the intersection of AI with competitive marketing strategies, emphasizing its pivotal role in innovating e-commerce marketing models and gathering customer data for strategic development and the diverse challenges and opportunities of AI adoption in marketing activities. In summary, these studies highlight the transformative potential of AI in revolutionizing marketing strategies, providing companies with a competitive edge. However, persistent challenges such as varying adoption rates, knowledge gaps, and the need to balance technology with human elements in marketing endeavors continue to shape the landscape of AI implementation in marketing. Future research directions for cluster seven could include the following:

1. The role of AI in innovative e-commerce marketing models and market segmentation strategies.
2. The impact of AI on the development of marketing strategies in specific sectors like retail.
3. The challenges and opportunities in adopting AI for strategic marketing decisions, particularly in the B2B context.

The findings across the clusters indicate a comprehensive integration of AI and machine learning across various domains of digital marketing and consumer engagement. The promi-

nence of machine learning in the AI/ML algorithms cluster underscores its foundational role in powering various digital marketing strategies, with an emphasis on using data-driven insights to understand consumer behavior and improve decision-making processes.

This emphasis on consumer understanding is further highlighted in the consumer behavior cluster, where there is a significant focus on using natural language processing to better comprehend consumer needs and language nuances. This capability is crucial for personalizing experiences in e-commerce, as indicated by the presence of chatbots and purchase intention keywords in the e-commerce cluster, suggesting that businesses are increasingly relying on AI to enhance customer interaction and optimize the shopping experience.

Figure 7 presents a graphical abstract illustrating the prospects of AI in digital marketing.

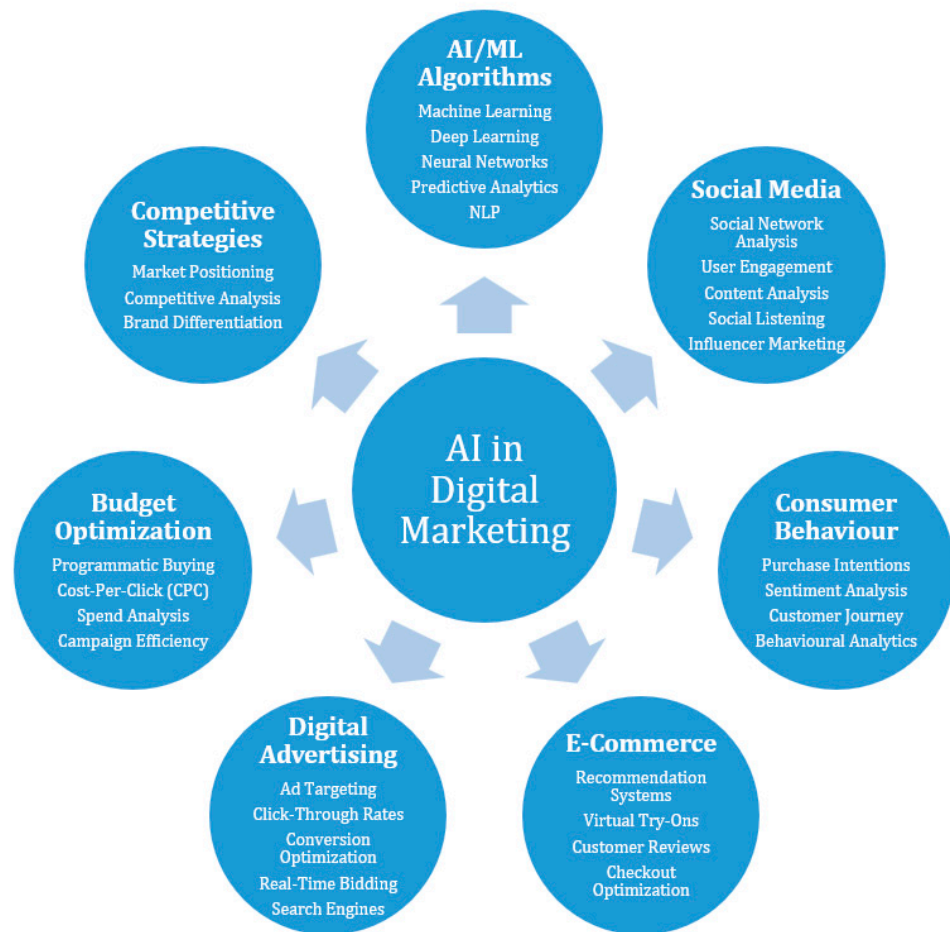


Figure 7. Prospects of AI in digital marketing.

Social media emerges as a pivotal channel for these interactions, with the centrality of social media marketing pointing to its use as a platform for leveraging AI for targeted marketing and customer data analytics. The integration of intelligent systems and online systems in this cluster suggests an ongoing trend toward automation and sophisticated data management in engaging with consumers on social media.

The digital advertising cluster’s focus indicates the industry’s shift toward AI-driven advertising campaigns, where the technology is used to optimize marketing communications and search engine strategies for more effective consumer targeting and engagement.

The optimization and budget control cluster ties these themes together, emphasizing the need for efficiency and cost management in deploying AI strategies. This is where the operational side of digital marketing comes into play, using AI for budget control and ensuring that marketing strategies are not only effective but also economically viable.

Lastly, the competitive strategies cluster reflects the broader business implications of AI in digital marketing, where companies seek to gain competitive advantages and drive profitability through strategic planning and sustainable development.

In synthesis, the findings across these clusters reveal a digital marketing ecosystem heavily influenced by AI's analytical and predictive capabilities. This ecosystem is characterized by a strong focus on consumer-centric strategies, data-driven decision-making, and the efficient allocation of resources to maintain competitiveness and drive sustainable growth in the digital age.

5. Conclusions

In the intersection of artificial intelligence (AI) and digital marketing, our systematic review illuminated a series of core domains. At the forefront, AI and machine learning (ML) algorithms have become the backbone of modern digital marketing, with techniques like deep learning and neural networks integral to predictive analytics and the personalization of strategies [11]. Within the realm of social media, AI-enabled tools have overhauled engagement tracking and analytics, offering marketers a profound grasp of consumer insights and ensuring campaigns are fine-tuned to audience needs [22]. This understanding is further evident in the sphere of consumer behavior, where AI models now delineate consumer preferences, loyalty, and purchase trajectories with unprecedented precision [33]. The e-commerce sector has also been transformed by AI, notably in recommendation systems and chatbots which have optimized user experiences and augmented conversion rates [41]. In the realm of online and search advertising, strategies involving smart speakers and voice data mining have emerged, bolstering multi-sensory interactions. These advancements cultivate a more immersive and enriched user experience in advertising [47,48]. Crucially, budgetary constraints and the need for optimization in marketing campaigns have been addressed by advanced AI algorithms, minimizing resource wastage [57]. Finally, the strategic deployment of AI in market analysis has granted businesses the capability to gain a competitive advantage [61].

Despite the comprehensive nature of our review, we acknowledge certain limitations. Firstly, our study is constrained by the scope of the literature reviewed, which may not encompass all recent advancements in AI applications in digital marketing. Additionally, as with any literature review, potential biases in source selection and interpretation could influence our findings. Lastly, the rapidly evolving nature of AI technologies means that some insights may become outdated swiftly, limiting the long-term applicability of our conclusions. These limitations should be considered when interpreting our results and serve as potential directions for future research in this dynamic field. Looking ahead, the research horizon in digital marketing and AI is teeming with potential. Embracing diverse and emerging markets in future research can address cultural imbalances. Longitudinal studies tracing AI's evolution could offer time-sensitive insights, especially in the realm of AI ethics, data privacy, and consumer consent. Collaborations between AI technologists and digital marketing experts are poised to spark a new wave of holistic, interdisciplinary research. Furthermore, the integration of AI with fields such as modeling, uncertainty handling, and hybrid systems presents intriguing prospects. Applying network and systems theory can enhance our understanding of consumer behavior, while leveraging insights from image processing and neuroscience could transform user engagement strategies.

Concurrently, the varied AI methodologies, viewed as a portfolio of technologies, have distinct purposes and applications in marketing. They are being developed and adopted at varying rates. As AI technologies, particularly generative AI, continue to evolve, their potential to reshape the digital marketing landscape grows, leading to significant implications for marketers. The recent advancements in AI, along with their increasing public accessibility, are drawing attention to the transformative impact of AI in the marketing sector. It is becoming evident that marketing leaders who utilize AI will likely have a distinct advantage over those who do not in the coming years.

A future research agenda should delve into the depth of AI application in marketing and its implications for practitioners. This includes developing a comprehensive framework for the systematic use of AI in marketing, linking each AI technology to specific marketing domains, and exploring their extent of implementation. This should be complemented by representative AI examples for every marketing purpose, highlighting the potential for AI in digital marketing to move beyond current paradigms and open new avenues for research and application.

Author Contributions: Conceptualization, C.Z. and M.V.; methodology, C.Z.; software, C.Z.; validation, C.Z. and M.V.; formal analysis, C.Z.; investigation, C.Z. and M.V.; resources, C.Z.; data curation, M.V.; writing—original draft preparation, C.Z.; writing—review and editing, C.Z. and M.V.; visualization, C.Z.; supervision, M.V.; project administration, C.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data for the bibliometric analysis presented in this study are available on request from the corresponding author. The data are not publicly available since they have been extracted from Scopus database (accessed on 25 August 2023).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Core Sources by Bradford’s Law.

SO	Rank	Freq	cumFreq	Zone
Journal of Business Research	1	10	10	Zone 1
Applied Marketing Analytics	2	9	19	Zone 1
Journal of Retailing and Consumer Services	3	7	26	Zone 1
Industrial Marketing Management	4	6	32	Zone 1
Australasian Marketing Journal	5	5	37	Zone 1
Journal of the Academy of Marketing Science	6	5	42	Zone 1
Psychology and Marketing	7	5	47	Zone 1
European Journal of Marketing	8	3	50	Zone 1
IEEE Access	9	3	53	Zone 1
International Journal of Information Management	10	3	56	Zone 1
International Journal of Research In Marketing	11	3	59	Zone 1
Journal of Brand Strategy	12	3	62	Zone 1
Journal of Interactive Marketing	13	3	65	Zone 1
Journal of Product and Brand Management	14	3	68	Zone 1
Journal of Research in Interactive Marketing	15	3	71	Zone 1
Mobile Information Systems	16	3	74	Zone 2
Sustainability	17	3	77	Zone 2
Technological Forecasting and Social Change	18	3	80	Zone 2
Electronic Commerce Research and Applications	19	2	82	Zone 2
Frontiers in Psychology	20	2	84	Zone 2
Information Processing and Management	21	2	86	Zone 2
Information Systems Frontiers	22	2	88	Zone 2
International Journal of Computational Intelligence Systems	23	2	90	Zone 2
International Journal of Emerging Markets	24	2	92	Zone 2
International Journal of Engineering And Advanced Technology	25	2	94	Zone 2
International Journal of Market Research	26	2	96	Zone 2
Journal of Brand Management	27	2	98	Zone 2
Journal of Business Ethics	28	2	100	Zone 2

Table A1. Cont.

SO	Rank	Freq	cumFreq	Zone
Journal of Marketing	29	2	102	Zone 2
Journal of Marketing Theory And Practice	30	2	104	Zone 2
Journal of Services Marketing	31	2	106	Zone 2
Scientific Programming	32	2	108	Zone 2
Security and Communication Networks	33	2	110	Zone 2
Advances in Distributed Computing and Artificial Intelligence Journal	34	1	111	Zone 2
ARNP Journal of Engineering And Applied Sciences	35	1	112	Zone 2
Artificial Intelligence Review	36	1	113	Zone 2
Bottom Line	37	1	114	Zone 2
Business: Theory and Practice	38	1	115	Zone 2
California Management Review	39	1	116	Zone 2
Central European Business Review	40	1	117	Zone 2
Computational Intelligence and Neuroscience	41	1	118	Zone 2
Computer Speech and Language	42	1	119	Zone 2
Computers	43	1	120	Zone 2
Computers and Electrical Engineering	44	1	121	Zone 2
Computers and Industrial Engineering	45	1	122	Zone 2
Decision Support Systems	46	1	123	Zone 2
Designs	47	1	124	Zone 2
Eastern-European Journal of Enterprise Technologies	48	1	125	Zone 2
Egyptian Informatics Journal	49	1	126	Zone 2
Electronic Commerce Research	50	1	127	Zone 2
Electronics	51	1	128	Zone 2
Emerging Science Journal	52	1	129	Zone 2
Engineering Applications of Artificial Intelligence	53	1	130	Zone 2
European Journal of Operational Research	54	1	131	Zone 2
Expert Systems with Applications	55	1	132	Zone 2
F1000Research	56	1	133	Zone 2
Foresight	57	1	134	Zone 2
Foundations and Trends in Marketing	58	1	135	Zone 2
Fujitsu Scientific and Technical Journal	59	1	136	Zone 2
Humanities and Social Sciences Communications	60	1	137	Zone 2
IAES International Journal of Artificial Intelligence	61	1	138	Zone 2
IEEE Intelligent Systems	62	1	139	Zone 2
IEEE Transactions on Computational Social Systems	63	1	140	Zone 2
IEEE Transactions on Engineering Management	64	1	141	Zone 2
IEEE Transactions on Neural Networks and Learning Systems	65	1	142	Zone 2
Industrial Management And Data Systems	66	1	143	Zone 3
Informatics	67	1	144	Zone 3
Information Sciences Letters	68	1	145	Zone 3
Informatologia	69	1	146	Zone 3
Innovative Marketing	70	1	147	Zone 3
Intelligent Automation and Soft Computing	71	1	148	Zone 3
Intelligent Systems with Applications	72	1	149	Zone 3
International Journal of Advanced Computer Science and Applications	73	1	150	Zone 3
International Journal of Advanced Trends in Computer Science and Engineering	74	1	151	Zone 3
International Journal of Advances in Soft Computing and its Applications	75	1	152	Zone 3
International Journal of Advertising	76	1	153	Zone 3
International Journal of Computer Information Systems and Industrial Management Applications	77	1	154	Zone 3
International Journal of E-business Research	78	1	155	Zone 3
International Journal of Electronic Business	79	1	156	Zone 3
International Journal of Electronic Customer Relationship Management	80	1	157	Zone 3
International Journal of Engineering Trends and Technology	81	1	158	Zone 3
International Journal of Hospitality Management	82	1	159	Zone 3
International Journal of Human-computer Interaction	83	1	160	Zone 3
International Journal of Information Management Data Insights	84	1	161	Zone 3

Table A1. Cont.

SO	Rank	Freq	cumFreq	Zone
International Journal of Innovative Technology and Exploring Engineering	85	1	162	Zone 3
International Journal of Recent Technology and Engineering	86	1	163	Zone 3
International Journal of Retail and Distribution Management	87	1	164	Zone 3
Journal of Advertising	88	1	165	Zone 3
Journal of Ambient Intelligence and Smart Environments	89	1	166	Zone 3
Journal of Business and Industrial Marketing	90	1	167	Zone 3
Journal of Computational Methods in Sciences and Engineering	91	1	168	Zone 3
Journal of Consumer Behaviour	92	1	169	Zone 3
Journal of Consumer Marketing	93	1	170	Zone 3
Journal of Content, Community and Communication	94	1	171	Zone 3
Journal of Enterprise Information Management	95	1	172	Zone 3
Journal of Entrepreneurship in Emerging Economies	96	1	173	Zone 3
Journal of Financial Services Marketing	97	1	174	Zone 3
Journal of Global Information Management	98	1	175	Zone 3
Journal of Global Scholars of Marketing Science: Bridging Asia and The World	99	1	176	Zone 3
Journal of Hospitality and Tourism Technology	100	1	177	Zone 3
Journal of Industrial Engineering and Engineering Management	101	1	178	Zone 3
Journal of Marketing Analytics	102	1	179	Zone 3
Journal of Metaverse	103	1	180	Zone 3
Journal of Organizational and End User Computing	104	1	181	Zone 3
Journal of Retailing	105	1	182	Zone 3
Journal of Sensors	106	1	183	Zone 3
Journal of Service Management	107	1	184	Zone 3
Journal of Strategic Marketing	108	1	185	Zone 3
Journal of Supercomputing	109	1	186	Zone 3
Journal of Telecommunication, Electronic and Computer Engineering	110	1	187	Zone 3
Journal of The Association for Information Science and Technology	111	1	188	Zone 3
Journal of The Knowledge Economy	112	1	189	Zone 3
Journal of Theoretical and Applied Electronic Commerce Research	113	1	190	Zone 3
KSII Transactions on Internet and Information Systems	114	1	191	Zone 3
Lecture Notes on Data Engineering and Communications Technologies	115	1	192	Zone 3
Management Decision	116	1	193	Zone 3
Materials Today: Proceedings	117	1	194	Zone 3
NEC Technical Journal	118	1	195	Zone 3
Network Security	119	1	196	Zone 3
Neural Network World	120	1	197	Zone 3
Qualitative Market Research	121	1	198	Zone 3
Research Technology Management	122	1	199	Zone 3
SAGE Open	123	1	200	Zone 3
Singapore Economic Review	124	1	201	Zone 3
Spanish Journal of Marketing—Esic	125	1	202	Zone 3
Studies in Computational Intelligence	126	1	203	Zone 3
Systems Research and Behavioral Science	127	1	204	Zone 3
Technology Analysis and Strategic Management	128	1	205	Zone 3
Telematics and Informatics	129	1	206	Zone 3
TEM Journal	130	1	207	Zone 3
TQM Journal	131	1	208	Zone 3
Uncertain Supply Chain Management	132	1	209	Zone 3
Wireless Communications and Mobile Computing	133	1	210	Zone 3
World Journal of Entrepreneurship, Management and Sustainable Development	134	1	211	Zone 3

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