

Mapping Digital Marketing Analytics Literature: A Bibliometric Study of Research Trends, Gaps, and Emerging Theme

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Abstract

The objective of this paper is to conduct a bibliometric analysis of digital marketing analytics (DMA) and its correlation with marketing-related practices. The current study aims to provide an in-depth review of earlier research conducted in the field of DMA and associated areas. An analysis was conducted based on the year of release, distribution of authors, leading publishers, top authors, and the clustering of frequently used keyword. The database determines the total number of authors as 185, who participate in the topic using the parameter of at least two articles published in the chosen subject matter. Twenty-two of these requirements are met. VOSviewer discovers 654 keywords, of which 22 fulfill the requirement with a minimum occurrence of four. This literature review consolidates research from Scopus-indexed publications, emphasizing the development, methodology, applications, and issues related to DMA.

Categories: Social media and customer relationship management, Digital Marketing, Marketing and Market Issues in Business

Keywords: digital marketing, marketing analytics, web analytics, data analytics, social media analytics

Introduction And Background

Digital marketing analytics (DMA) has been a vital area within marketing research, especially in the last 15 years. The increase in interest is mostly fueled by the swift expansion of online platforms and the significant rise in data accessibility. The incorporation of data-driven decision-making has transformed marketing strategies, allowing firms to acquire profound insights into customer behavior and enhance their digital efforts. The academic community has endeavored to comprehend, assess, and enhance the techniques employed in DMA in light of this transition. The early 2010s signified a notable transformation in marketing strategies as enterprises progressively adopted digital channels to interact with consumers. This transition was enabled by progress in web analytics, which equipped marketers to monitor and quantify consumer interactions across websites, social media, and e-commerce platforms. Authors emphasized the need of using web analytics into marketing strategies to augment consumer engagement and elevate conversion rates (Chaffey D and Patron M, 2012). Their research established the groundwork for further investigations that assessed the efficacy of digital marketing techniques by empirical data analysis.

The proliferation of social media platforms has heightened the demand for sophisticated analytical techniques. Researchers investigated key performance indicators for evaluating social media efficacy, highlighting the significance of engagement metrics rather than simply reach or impressions (Hoffman and Fodor, 2010). Their study emphasized the dynamic aspect of digital marketing, wherein consumer interactions and sentiment analysis become important for assessing performance. This transition required the creation of advanced analytical tools capable of handling extensive unstructured data from many digital sources. As digital marketing becomes increasingly sophisticated, academics have employed several approaches to examine online consumer behavior. Data mining tools have been useful in revealing trends within customer data. Scholars illustrated the application of clustering and association rule mining for customer segmentation based on online behaviors, enabling marketers to customize targeted marketing (Ngai et al., 2011). These methods have demonstrated efficacy in enhancing marketing initiatives by forecasting consumer inclinations and recognizing nascent trends.

Machine learning methodologies have significantly improved the forecasting capacities of DMA. Decision trees and neural networks have been employed to model consumer behavior and enhance marketing strategies (Liu and Shih, 2013). These technologies allow marketers to automate decision-making and enhance targeting strategies, leading to a more efficient allocation of marketing resources. The utilization of artificial intelligence (AI) in marketing analytics is advancing, with new research concentrating on deep learning models to improve predictive precision. Sentiment analysis has been a pivotal focus in DMA, especially due to the proliferation of social media. Researchers have utilized natural language processing techniques to evaluate consumer attitudes extracted from online reviews, social media posts, and

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customer feedback ([Mostafa, 2013](#)). This method enables marketers to assess public impression of companies, goods, and campaigns instantaneously. Through the analysis of sentiment trends, firms can modify their marketing strategies to correspond with consumer expectations and desires.

The emergence of big data has profoundly impacted the domain of DMA. The capacity to process and analyze extensive volumes of structured and unstructured data has created new opportunities for comprehending consumer behavior. Businesses currently have access to data from various sources, including social media interactions, website traffic, mobile applications, and online purchases. The abundance of data has required the creation of sophisticated analytical methods to derive useful insights. Real-time analytics has emerged as an essential element of digital marketing tactics. Marketers can now monitor user interactions in real time, allowing for immediate data-driven decision-making. Programmatic advertising uses real-time bidding algorithms to enhance ad placements according to user activity and preferences. This method improves the efficacy of digital advertising campaigns by guaranteeing that advertisements reach the appropriate audience at the optimal moment. Moreover, personalization has emerged as a central emphasis in DMA. By utilizing big data and machine learning algorithms, organizations can develop personalized marketing experiences customized to particular consumer interests. Recommendation algorithms employed by e-commerce platforms, such as Amazon, and streaming services like Netflix, evaluate user behavior to propose pertinent products and content. These tailored experiences augment consumer pleasure and elevate engagement rates. Notwithstanding the progress in DMA, numerous obstacles endure. A primary concern is data privacy and security. The gathering and examination of consumer data prompt ethical inquiries regarding user consent and data safeguarding. The enactment of rules like the General Data Protection Regulation has mandated more rigorous data governance policies, compelling enterprises to guarantee openness and adherence in their data management procedures.

A further concern pertains to the quality and reliability of data. Digital marketing data is frequently unstructured and scattered across various platforms, complicating effective consolidation and analysis. Ensuring data precision and uniformity is essential for obtaining significant insights. Researchers have investigated diverse data preparation methods, including data cleansing and normalization, to improve the quality of digital marketing datasets. The swiftly changing characteristics of digital platforms present a challenge for scholars and practitioners. Emerging technologies and evolving customer habits consistently transform the digital marketing landscape, necessitating ongoing adjustments to analytical approaches. The advent of voice search, augmented reality, and virtual reality has created new facets of digital marketing, requiring novel methodologies for data analysis. As DMA progresses, certain new themes merit additional investigation. The incorporation of AI-driven automation in marketing decision-making is one such domain. The implementation of AI-driven chatbots, virtual assistants, and automated content creation has revolutionized customer interactions, providing fluid and tailored experiences. Subsequent studies may investigate the efficacy of AI-driven marketing techniques and their influence on consumer involvement.

The significance of influencer marketing in digital analytics is increasing. Social media influencers significantly affect consumer views and purchasing decisions ([Lou and Yuan, 2019](#)). Evaluating influencer engagement metrics, audience demographics, and content efficacy may yield significant insights for enhancing influencer marketing initiatives. Researchers may investigate the effects of influencer partnerships on brand efficacy and consumer confidence ([Boerman et al., 2017](#)). The amalgamation of web analytics, machine learning, sentiment analysis, and big data methodologies has transformed marketing methods, allowing enterprises to enhance their digital efforts ([Järvinen and Karjaluoto, 2015](#)). Nonetheless, concerns concerning data privacy, quality, and shifting consumer behaviors endure, requiring continuous research and innovation ([Wedel M and Kannan PK, 2016](#)).

Review

The swift transformations in contemporary business, driven by emerging trends, cutting-edge technology, and digitalization, compel organizations to adopt digital practices. Marketers encounter hurdles in seeking innovative methods to engage their clients. For modern marketers, digital marketing is an essential function within a business that enables effective consumer engagement, brand recognition, and customer loyalty. The advantageous impact of brand identification via digital marketing may lead to customer-generated word-of-mouth promotion for the brand ([Moncey and Baskaran, 2020](#)).

In today's digital environment, marketing analytics are essential and varied ([Saura JR et al., 2017](#)). A comprehensive collection of marketing literature explores the practical aspects of marketing analytics, including essential definitions ([Iacobucci et al., 2019](#)), specific applications ([Mikalef P et al., 2018](#)), and organizational implementation ([Branda et al., 2018](#)). However, there is a paucity of discourse regarding the integration of analytics with marketing theory ([Iacobucci et al., 2019](#)). The marketing analytics literature lacks a conceptual and functional framework rooted in foundational marketing principles, linking the selection and application of marketing analytics to an establishment's overarching marketing strategy.

Marketing analytics, described as “the study of data and modelling tools used to address marketing resource and customer-related business decisions” has been documented in literature and industry since the early twentieth century (Iacobucci et al., 2019). The emergence of marketing analytics as a distinct field occurred with the advent of the internet and the introduction of technologies like CRMs and search engines (Wedel M and Kannan PK, 2016). Since then, attention in marketing analytics has surged (Petrescu M and Krishen AS, 2017) as researchers investigated the use of various marketing analytics methodologies across multiple industries. This expansion was primarily fueled by the massive increase in available data and marketers’ endeavors to address the fundamental question of how to utilize it effectively (Petrescu M and Krishen AS, 2017). Exploring that question has yielded research concentrating on the methodologies and objectives of marketing analytics, providing definitions, approaches, applications, and evaluations of the impact of marketing analytics (Wedel M and Kannan PK, 2016). The literature has consistently overlooked the establishment of a guiding consensus regarding the most valuable techniques (Saura JR et al., 2017) and the effective integration of DMA into an organization’s comprehensive marketing strategy (Kingsnorth, 2019) and (Iacobucci et al., 2019).

DMA has been utilized in various sectors:

1. Customer Segmentation: Through the analysis of online activity, enterprises can more efficiently categorize customers. Researchers have examined sophisticated segmentation methods that utilize digital footprints to customize marketing campaigns (Wedel M and Kannan PK, 2016).
2. Campaign Optimization: Real-time analytics empower marketers to dynamically modify campaigns. A study by Järvinen and Karjaluo (Järvinen J and Karjaluo H, 2015) illustrated how organizations utilize analytics to enhance email marketing efforts, leading to increased open and click-through rates.
3. Social Media Strategy: Comprehending the influence of social media endeavors is essential. Scholars introduced a methodology for social media analytics that aids organizations in evaluating engagement and guiding strategy formulation (Peters et al., 2013).

Notwithstanding its benefits, DMA encounters some challenges:

1. Data Privacy: The aggregation and examination of consumer data engender privacy apprehensions. Tene and Polonetsky (Tene O and Polonetsky J, 2012) examined the equilibrium between data-driven marketing and customer privacy, emphasizing the necessity for ethical data methods.
2. Data Integration: Merging data from several digital channels might be intricate (Tene O and Polonetsky J, 2012).
3. Skill Gap: There exists a demand for workers proficient in both marketing and analytics. Columbus (Columbus, 2014) underscored the significance of interdisciplinary training to close this gap.

The future of DMA will be influenced by developments in AI and big data technology. Davenport et al. (Davenport et al., 2020) proposed that predictive analytics and automated decision-making will increasingly dominate, facilitating more tailored and efficient marketing methods. The emergence of the Internet of Things offers novel prospects for data collection and analysis, as articulated by Atzori et al. (Atzori et al., 2010). In the last 15 years, DMA has become an essential element of contemporary marketing. It has facilitated businesses in making data-driven decisions, optimizing campaigns, and improving client engagement using many approaches and applications. Nonetheless, obstacles concerning data protection, integration, and competence deficiencies remain. Resolving these difficulties will be crucial as the sector progresses, propelled by technical innovations and shifting customer behaviors. Pursuant to the findings of a search undertaken in January 2025 on the Scopus database, there have been 200 articles on the matter of DMA throughout the previous 15 years, or from 2010 to 2024. In-depth analysis of these publications is necessary to uncover novel data, emerging patterns, and fresh research. As a result, it can be concluded that no Bibliometric targeting the scope of research trends pertaining to DMA has been discovered. As a result, the study’s objectives were to examine, assess, and contrast numerous DMA-related research papers that were published as original articles in journals with a Scopus index. Hopefully, this Bibliometric will aid in the development of DMA-related research. The following research goals became the foundation for this review.

Objective

The main aim of this paper is to perform a thorough bibliometric examination of the academic discussion regarding the phrase DMA and its associated terminology. It seeks to examine annual publishing trends to ascertain the growth trajectory, frequency, and change of scholarly interest in this field over time. This aids in comprehending the evolution of the topic and identifying the years that garnered substantial academic focus. Secondly, the study aims to identify and analyze the contributions of notable authors who have substantially improved research in DMA. Identifying significant contributions offers insight into thought leadership and intellectual impact within the field. The research aims to identify the leading publication outlets - such as journals and conferences - that regularly publish information on DMA, thereby pinpointing the principal channels for disseminating important knowledge. The study seeks to analyze existing literature to identify current research trends and identify prospective research gaps. This not only highlights present study focal points but also identifies underexplored subjects, providing

significant avenues for future enquiries in DMA.

Methodology

A bibliometric study was performed. The Scopus database was employed to execute the inclusion-exclusion search, conducted using Harzing’s Publish or Perish (Harzing, 2007). Publications from publishers such as Elsevier, Emerald Insight, Springer, Taylor & Francis, and Sage were assessed. The literature review was conducted from 2010 to 2024 with the search terms "Digital marketing analytics" (DMA) and "Marketing Analytics." This review examined academic literature regarding DMA that was published in English in journals indexed by Scopus, Web of Science, or the Australian Business Deans Council. Criteria for exclusion: In the second phase, we ascertained the absence of duplicates. Subsequently, articles in English from Scopus-indexed journals were assessed. This inquiry produced 200 pertinent articles. The gathered data were exported in *CSV format for subsequent processing or simulation in VOSviewer and *RIS. The VOSviewer program is utilized for data visualization. The criteria for inclusion and exclusion pertain to publications concerning "Digital marketing analytics" (DMA), peer review, and the English language. Articles not connected to "Digital marketing analytics" (DMA), including those concerning conferences, non-English content, and book chapters, were removed. Articles lacking an ISSN, DOI, start page-end page, or containing incorrect volume information were excluded from final selection.

Inclusion criteria: Papers related to "Digital marketing analytics" (DMA), only peer-reviewed papers and Scopus indexed, English language papers only.

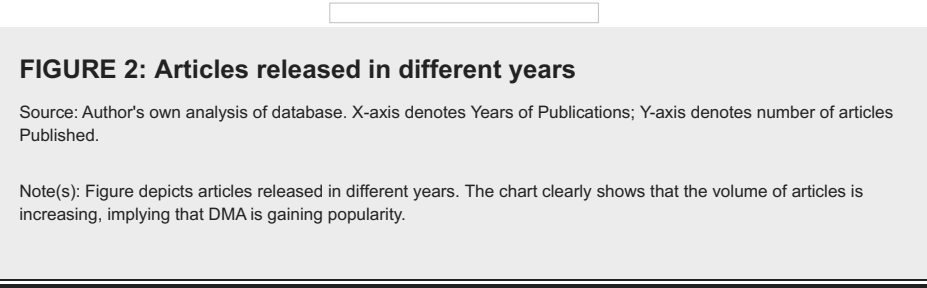
Exclusion criteria: Conference papers, book chapters, review papers, non-English papers (Figure 1).



Descriptive analysis

Year Wise Publication Trends

Annual research trends indicate that publications in "Digital Marketing Analytics" (DMA) significantly rose starting in 2010 and have since remained consistently stable and progressive. The insufficient number of annual publications indicates that the domain of "Digital Marketing Analytics" (DMA) remains underexplored. The years with the most contributions were 2021 and 2020, with 38 and 30 articles, respectively. In 2023, 18 publications were released, however, just 5 were published in 2024. See Figure 2.



Top Ten Contributing Authors

The table below enumerates the 10 foremost authors in DMA, sorted according to citation frequency. D. Boyd has 3,959 citations, A. Kumar has 703, and P.S.H. Leeftang has 425. This table underscores the notable contributions of these authors to the domain of DMA, with D. Boyd being the most frequently mentioned. See Table 1.

Authors	Citations
D. Boyd	3959
A. Kumar	703
P.S.H. Leeflang	425
L. Ardito	405
Z. Xu	351
E. Marine-Roig	277
D. Chaffey	264
D.P. Sakas	251
K. Li	222
R. Aswani	216
Note(s): Table displays the authors contributing in Digital Marketing Analytics, D. Boyd, leads the list with 3959 citations.	

TABLE 1: Top 10 authors contributing in "Digital Marketing Analytics"

Source: Authors' own analysis of the database

Top Contributing Journals

The table below displays the citation counts from different journals on the subject of DMA. The foremost entry is "Information Communication and Society" with 4,021 citations. The "Journal of Marketing" has 764 citations, whereas "Industrial Marketing Management" has 647 citations. The cumulative count of citations is 7,824. This table highlights the significance of these journals in academic citations, with "Information Communication and Society" being the most frequently referenced. See Table 2.

Source	Citations
Information Communication and Society	4,021
Journal of Marketing	764
Industrial Marketing Management	647
Journal of Business Research	570
European Management Journal	425
Business Process Management Journal	405
International Journal of Information Management	285
Journal of Destination Marketing and Management	277
Electronic Commerce Research and Applications	222
Journal of the Academy of Marketing Science	208
Note(s): Table indicates the number of citations associated with diverse journals. Information Communication and Society leads the list with 4,021 citations.	

TABLE 2: Top contributing journals on theme "Digital Marketing Analytics"

Source: Authors own analysis using VOSviewer

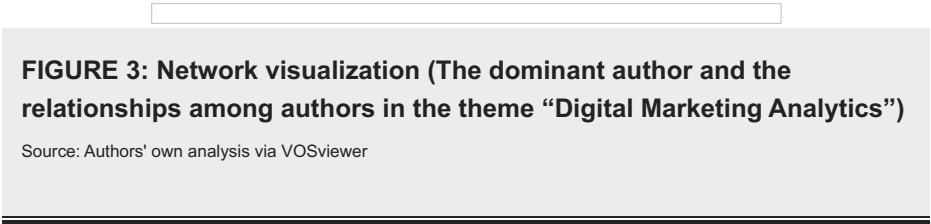
Bibliometric Analysis

The analysis aims to find research publications that are highly cited internationally, often referenced locally, and well-regarded in a certain research domain. Local reference can be performed using citation or

co-citation analysis in VOSviewer, where VOS signifies the depiction of similarities. The preference for VOSviewer over other software is based on the explanation provided by Van Eck and Waltman (Van Eck and Waltman, 2010). VOSviewer may present a map in multiple formats, each highlighting a certain component of the map. It provides functionalities for zooming, scrolling, and searching, enabling comprehensive study of a map. VOSviewer's visualization features are especially useful for maps containing a relatively significant number of elements (e.g., 100 or more). Many computer programs utilized for bibliometric mapping inadequately represent such maps. The network diagram below was generated using VOSviewer software. From the database, a total of 185 authors were recognized as participants in the selected topic, based on the criterion of a minimum publication of two papers in that area. Six authors fulfill the criterion. Primarily, there is an absence of co-citation or any other established relationships in the field. It exposes a significant research disparity among the authors. Refer to Figure 3, Figure 4, and Figure 5.

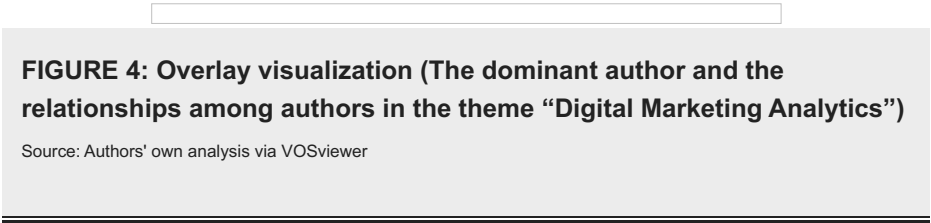
Network Visualization

The subsequent picture illustrates a network visualization created with VOSviewer, depicting the interconnections among several authors within the context of DMA. The authors' names are dispersed around the page, with some highlighted in different colors to denote specific groupings or clusters within the network. This static view does not display the specific connections between writers, which are typically represented as lines or links. The cited authors include:



Overlay Visualization

The visualization presented below was generated using VOSviewer, a software commonly employed for bibliometric analysis. It presents a visual overlay pertaining to the subject of "Digital Marketing Analytics" (DMA). This visualization displays the names of various authors along a timeline from 2010 until 2024. The diverse colors and sizes of each author's name indicate their degree of influence or the volume of work they have contributed to the specified theme. A timeline featuring color gradients at the bottom illustrates the temporal dimension of the data, extending from 2010 (left) to 2024 (right). The visualization is a static graphic, devoid of clear questions or interactive elements. This description, which highlights the overlay visualization of writers within the sphere of "Digital Marketing Analytics" (DMA), aligns with the initial metadata findings spanning two decades.



Density Visualization

VOSviewer, a software commonly employed for bibliometric analysis, was utilized to create the density visualization depicted in the image below. It illustrates the interrelations among several authors within the context of "Digital marketing analytics" (DMA). Regions of increased density, indicative of more robust or consistent author collaborations or thematic intersections, are emphasized in brighter hues such as yellow and green within the color gradient visualization. A multitude of authors' names is presented in the visualization, signifying their substantial contributions to or associations with the subject of investigation. The picture effectively depicts the categorization and interconnections among the mentioned writers, based on their study connected to "Digital marketing analytics" (DMA), despite the absence of specific data points and mathematical analysis.

FIGURE 5: Density visualization (The dominant author and the relationships among authors in the theme “Digital Marketing Analytics”)

Source: Authors' own analysis via VOSviewer

Meta-analysis

Selected Terms/Keywords

The table enumerates 22 selected terms/keywords pertinent to a study, extracted using VOSviewer from an original collection of 654 keywords. Refer to Table 3. The keywords were chosen based on a minimum frequency of four occurrences. This procedure guarantees that the research concentrates on the most pertinent and commonly appearing terms inside the dataset. See Table 3.

S. no	Terms
1	analytic
2	application
3	artificial intelligence
4	big data
5	big data analytic
6	case study
7	content
8	data
9	data analytic
10	digital marketing
11	digital transformation
12	effect
13	future
14	impact
15	implementation
16	innovation
17	insight
18	marketing
19	role
20	social medium
21	use
22	web analytic

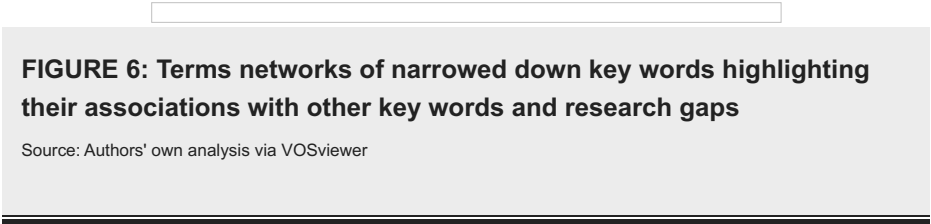
TABLE 3: Selected terms/keywords

Source: Authors' own analysis using VOSviewer

Term Analyse

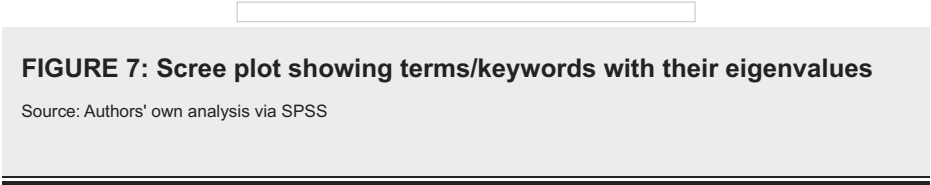
Analysis of the database revealed that VOSviewer identified 654 keywords, of which 22 met the criteria with a minimum occurrence of 4. Ding and Cronin (Ding Y and Cronin B, 2011) assert that an article's

reputation correlates with the volume of citations it receives from other publications. The frequency with which other articles cite a single article reflects its popularity and importance. Direct citation is the most valid way for assessing relatedness, as it acts as the primary (direct) indication, whilst co-citation and bibliographic connection serve as secondary (indirect) indicators of relatedness. Refer to Figure 6. Below is a network diagram generated using the bibliometric network visualization program VOSviewer.



Content Analysis

Keywords with many eigenvalues are the most often utilized in the specified domain, whilst those with fewer than one eigenvalue indicate possible research deficiencies. Refer to Table 3. The chart indicates that seven keywords possess the most value. Refer to Figure 7 and Table 4. Additionally, to create clusters, a factor analysis was conducted utilizing the main component approach in SPSS. This resulted in the "total variance explained," "component matrix," and "rotated component matrix." See Table 5 and Table 6.



S. no	Terms	Eigenvalue
1	analytic	More than one or equal to 1
2	application	
3	artificial intelligence	
4	big data	
5	big data analytic	
6	case study	
7	content	
8	data	
9	data analytic	Less than 1
10	digital marketing	
11	digital transformation	
12	effect	
13	future	
14	impact	
15	implementation	
16	innovation	
17	insight	
18	marketing	
19	role	
20	social medium	
21	use	
22	web analytic	

TABLE 4: Terms/keywords with their eigenvalue

Source: Authors' own analysis using VOSviewer

Factor Analysis

The table is comprehensive and provides a clear elucidation of how each aspect contributes to the total variation delineated by the factor analysis of phrases or keywords. This is frequently utilized in statistical analysis to ascertain the fundamental causes of the connection pattern among a collection of observable variables. The Total Variance Explained of Terms/Keywords by Factor Analysis is depicted in the image. This table systematically displays factor analysis data over numerous columns and rows.

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
analytic	5.422	24.647	24.647	5.422	24.647	24.647	3.674	16.700	16.700
application	4.378	19.900	44.548	4.378	19.900	44.548	3.638	16.536	33.236
artificial intelligence	3.726	16.939	61.486	3.726	16.939	61.486	3.180	14.454	47.690
big data	2.658	12.083	73.569	2.658	12.083	73.569	2.941	13.368	61.058
big data analytic	1.980	9.000	82.569	1.980	9.000	82.569	2.703	12.284	73.343
case study	1.612	7.326	89.895	1.612	7.326	89.895	2.500	11.364	84.707
content	1.279	5.813	95.709	1.279	5.813	95.709	2.420	11.002	95.709
data	.944	4.291	100.000						
data analytic	6.648E-16	3.022E-15	100.000						
digital marketing	4.599E-16	2.090E-15	100.000						
digital transformation	2.938E-16	1.336E-15	100.000						
effect	2.155E-16	9.795E-16	100.000						
future	1.678E-16	7.627E-16	100.000						
impact	5.979E-17	2.718E-16	100.000						
implementation	-8.981E-17	-4.082E-16	100.000						
innovation	-1.938E-16	-8.808E-16	100.000						
insight	-2.284E-16	-1.038E-15	100.000						
marketing	-2.631E-16	-1.196E-15	100.000						
role	-4.206E-16	-1.912E-15	100.000						
social medium	-5.681E-16	-2.582E-15	100.000						
use	-7.185E-16	-3.266E-15	100.000						
web analytic	-8.850E-16	-4.023E-15	100.000						
Extraction Method: Principal Component Analysis.									

TABLE 5: Total variance explained of terms/key words through factor analysis

Source: Authors' own analysis via SPSS

Clustering

Clusters are created by grouping papers according to their thematic similarities; hence, clustering serves as an effective technique for revealing unique aspects of subjects identified in contemporary literature. A total of 654 related articles were identified, and only these associated items were mapped. The employed technique was a "correlation of strength," with weight allocated to citations. The factor loadings of numerous terms and keywords over eight separate clusters, labeled from 1 to 7, are presented in the aforementioned Table 6. After the removal of negative values, each row signifies a unique phrase or keyword, while each column denotes a cluster, reflecting the extent of association between each term and the respective cluster. Principal Component Analysis was carried out utilizing Varimax with Kaiser Normalization. Following 17 iterations, the rotation converged. The thorough matrix presented below facilitates the understanding of relationships among numerous terms and clusters, providing a basis for future study analysis on these issues. Refer to Table 6 and Table 7.

Rotated Component Matrix ^a							
	Component						
	1	2	3	4	5	6	7
analytic					.220		
application					.907		
artificial intelligence							.812
big data	.991						
big data analytic							.846
case study	.855						
content						.516	
data			.858				
data analytic		.230					
digital marketing							.338
digital transformation	.855						
effect						.322	
future				.929			
impact		.910					
implementation		.910					
innovation			.768				
insight				.971			
marketing				.671			
role			.848				
social medium						.426	
use					.670		
web analytic					.660		
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 17 iterations.							

TABLE 6: Rotated component matrix of terms/keywords using principal component analysis

Source: Authors' own analysis via SPSS

Clustering of Key Terms							
	Clusters						
	1	2	3	4	5	6	7
Big data	.991						
case study	.855						
digital transformation	.855						
data analytics		.230					
impact		.910					
implementation		.910					
data			.858				
innovation			.768				
role			.848				
future				.929			
insight				.971			
marketing				.671			
Analytic					.220		
application					.907		
use					.670		
web analytic					.660		
Content						.516	
effect						.322	
social medium						.426	
artificial intelligence							.812
big data analytic							.846
digital marketing							.338

TABLE 7: Rotated component matrix showing clusters of terms/keywords

Source: Authors' own analysis via SPSS

Clustering of Terms

Cluster 1: big data, case study, digital transformation

Cluster 2: data analytics, impact, implementation

Cluster 3: data, innovation, role

Cluster 4: future, insight, marketing

Cluster 5: analytic, application, use, web analytic

Cluster 6: content, effect, social medium

Cluster 7: artificial intelligence, big data analytic, digital marketing

Research Gap

The research gap can be discerned by modifying the cut-off threshold, augmenting the amount of terms, altering the publication years, and employing a novel cluster combination. Terms and keywords with eigenvalues below one are rarely examined and tested. When rationally linked, these terms could become the future domain of investigation. We may amalgamate two or more clusters to formulate a new title or explore a novel study domain. The phrases data analytics, digital marketing, digital transformation, effect, future, impact, implementation, innovation, insight, marketing, role, social media, use, and web analytics all fell below the 1 eigenvalue threshold, signifying a substantial gap in the literature. These sentences facilitate the creation of new clusters. The title may be constructed utilizing these unexplored terms.

Conclusions

A thorough literature review was conducted utilizing the Scopus database through Harzing's Publish or Perish, with the search terms "Digital Marketing Analytics" and "Marketing analytics" from 2010 to 2024. The technique identified 200 pertinent papers. Yearly research trends indicate a substantial rise in publications post-2017; yet, the limited annual output implies that the phrase "Digital Marketing Analytics" remains inadequately investigated. From 2010 to 2017, the leading 10 journals constituted 57.831% of total research citations. The journal "Information Communication and Society" is the foremost contributor, with 4,021 citations. D. Boyd is the most prolific author, having received 3,959 citations. The database identified a total of 185 authors who contributed to the specified topic, based on the criterion of having published at least two publications in the relevant subject area. Six conditions have been fulfilled. VOSviewer identified 654 keywords, of which 22 meet the criterion of a minimum occurrence of 4. A total of 654 related articles were identified, and only these associated items were mapped. Terms and keywords with eigenvalues below one are rarely examined and tested.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Mohd Danish Chishti, Happy Sinha, Abdullah Bin Junaid

Acquisition, analysis, or interpretation of data: Mohd Danish Chishti, Happy Sinha, Abdullah Bin Junaid

Drafting of the manuscript: Mohd Danish Chishti, Happy Sinha, Abdullah Bin Junaid

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Disclosures

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