Volume 17 • Issue 4 • 2025

Engineering Management in Production and Services

sciendo

ISMSME International Society for Manufacturing, Service and Management Engineering

received: 8 June 2025
accepted: 20 November 2025

pages: 29-51

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Convergence of marketing technologies and artificial intelligence: a bibliometric review (1987-2025)

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ABSTRACT

This article explores the intersection of artificial intelligence (AI) and marketing technologies (MarTech) by conducting a comprehensive bibliometric analysis. The aim is to identify dominant research themes, key contributors, and major gaps in the existing literature. MarTech is conceptualised as a system of digital tools that enables marketing transformation. Scopus and Web of Science were used to collect records. Following a preliminary comparison, the final analytical corpus of peer-reviewed scientific publications (n=492) was drawn solely from Scopus. The study is based on a dataset from 1987 to 2025. Using Biblioshiny, the analysis examined publication dynamics, citation patterns, co-authorship networks, and thematic clusters. The results indicate consistent growth in scholarly attention, with an annual publication increase of 7.39 % across the full period and 36.53 % between 2015 and 2025. Five primary thematic clusters were identified: (1) AI-Marketing Core and Innovation, this cluster acts as a motor theme, integrating innovation, AI applications, and marketing outcomes, and providing conceptual and methodological scaffolding for the field; (2) Technology Adoption, functioning as a basic theme, it connects sources of innovation with market outcomes; (3) Market Applications and Digital Commerce, this cluster reflects the operationalisation of value in commerce and digital marketing, exhibiting high centrality and moving towards motor-theme status; (4) Perception and Human-Centred Factors, representing a niche but strategically important human perspective; it moderates the relationship between adoption and outcomes. (5) Generative Artificial Intelligence (e.g., ChatGPT), this is the most emerging stream, acting as an accelerator for innovation, adoption, and applications, while simultaneously elevating the importance of quality, safety, and ethics. The United States, India, and China lead in publication volume, while the United Kingdom, France, and Australia demonstrate the highest citation impact. Despite the growing literature base, theoretical fragmentation persists, and limited studies address the ethical, social, and emotional implications of AI in marketing.

KEY WORDS
marketing, marketing technologies, MarTech, artificial intelligence

10.2478/emj-2025-0025

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Introduction

The dynamic development of marketing technologies, commonly referred to as MarTech, is attracting increasing attention from researchers and marketing practitioners. Today, MarTech solutions powered by artificial intelligence (AI) are becoming central to both academic discourse and practical innovation in marketing. AI-enabled marketing technologies represent one of the most strategically and methodologically complex areas of investigation within the broader domain of management and marketing science.

Trojanowski, M. & Barmentloo, E. (2025). Convergence of marketing technologies and artificial intelligence: a bibliometric review (1987–2025). *Engineering Management in Production and Services, 17*(4), 29-51. doi: 10.2478/emj-2025-0025

These technologies are fundamentally transforming customer engagement, data-driven decision-making, and mass personalisation, thereby enhancing marketing effectiveness and organisational performance (Davenport et al., 2020; Kumar & Kotler, 2024; Wirth, 2018; Wirtz et al., 2018). As a result, marketing has emerged as one of the most technologically advanced functional areas of modern enterprises, undergoing a significant shift in required competencies.

This transformation necessitates not only advanced digital literacy among marketers but also a deep understanding of the technological landscape and rapidly evolving consumer behaviour. Key AI technologies accelerating this shift include machine learning, natural language processing (NLP), predictive analytics, and automated content generation. These tools increasingly underpin contemporary communication strategies by enabling real-time personalisation, automation of marketing processes, and data-driven decision-making (Huang & Rust, 2021, 2024; Kumar et al., 2024; Rust, 2020).

Despite their growing adoption, scholarly work on AI in marketing remains fragmented, spanning technological, ethical, consumer, and organisational domains (Chotisarn & Phuthong, 2025; Kietzmann et al., 2018; Lemon & Verhoef, 2016). An integrated perspective on the MarTech ecosystem - one that considers both theoretical foundations and practical applications - is, therefore, increasingly emphasised in the literature.

According to Chotisarn and Phuthong (2025), the study of marketing technologies is inherently interdisciplinary, drawing on frameworks such as service-dominant logic (Vargo & Lusch, 2004), dynamic capabilities theory (Teece, 2008; Teece et al., 1997), and technology acceptance models (de Andrés-Sánchez & Gené-Albesa, 2023). This orientation allows for a deeper understanding of complex phenomena related to digital transformation across various sectors, including retail, financial services, and tourism.

Given the rapid proliferation of publications in this field, a systematic review of the literature is warranted to identify dominant themes, structural trends, and knowledge gaps. The dynamic marketing environment presents both new avenues for academic inquiry and emerging directions for AI-driven tool development.

To assess the current state of research and the maturity of knowledge in this domain, the authors conducted a bibliometric analysis of peer-reviewed articles addressing the intersection of marketing technologies and AI. Using the Biblioshiny platform, the study examined publication trends, citation networks, co-authorship structures, and thematic clusters, culminating in a synthesised knowledge map that illustrates the evolving role of AI in marketing and outlines future research trajectories.

1. Research questions

In undertaking this bibliometric study, the authors adopted a descriptive bibliometric approach (Klincewicz, 2009), which enabled the identification of dominant research trends, leading scholars and institutions, and the assessment of the knowledge development trajectory in the domain of artificial intelligence (AI) applications in marketing technologies (MarTech). This method also facilitated the detection of research gaps and potential avenues for further investigation.

The analysis was based on bibliographic data retrieved from two leading scientific databases -Scopus and Web of Science - and included peer-reviewed publications from 1987 to 2025. The starting year corresponds to the earliest indexed works that jointly address both AI and MarTech. The dataset included metadata such as abstracts, keywords, author affiliations, and citation information, which were processed using the Biblioshiny platform. This enabled the visualisation of term co-occurrence networks, citation structures, and collaborative research patterns.

The study was guided by the following research questions:

- RQ1: What is the current state of research on the convergence of marketing technologies (MarTech) and artificial intelligence (AI)?
- RQ2: How has the literature in this area evolved over the past four decades?
- RQ3: Which research institutions and authors are the most active in publishing within the AI-MarTech domain?
- RQ4: What gaps and limitations exist in the current body of literature, and what opportunities do they offer for future research on AI-enabled marketing technologies?

The adopted approach provided a cross-sectional view of the current scholarly landscape, highlighting research intensity zones and revealing thematically significant areas that merit deeper theoretical and practical exploration.

2. Research methods

2.1. Search strategy and data collection

The research questions outlined above informed the scope of keywords and search queries used to curate a focused set of scientific publications. Searches were performed using English-language terms such as "AI", "artificial intelligence", and "marketing technology" across the Scopus and Web of Science databases.

The search and data preparation process followed a structured four-step procedure:

- Identification of relevant bibliographic databases (Scopus and Web of Science);
- Selection of bibliometric analysis tools (Bibliometrix R. Package, R language, Biblioshiny App: Bibliometrix for non-coders: Most relevant authors, Authors' production over time, Co-Citation Network, Collaboration Network, Clustering algorithm, Most Frequent Words, Co-occurrence network, Thematic map, Thematic evolution, etc.),
- Development and testing of inclusion keywords and phrases;
- Application of inclusion and exclusion criteria based on content relevance and academic quality (Klincewicz et al., 2012; Żemigała, 2018).

This process established a consistent and replicable framework for assembling a high-quality research dataset suitable for bibliometric analysis.

The bibliometric method was selected consciously, guided by the nature of the investigated phenomenon and its current stage of development within the academic discourse. The convergence of artificial intelligence (AI) and marketing technologies (MarTech) constitutes a relatively recent, dynamic, and multifaceted research area that necessitates, as an initial step, the systematisation of existing scholarly contributions, the identification of dominant research streams, and the detection of potential thematic gaps. With these factors in mind, the authors adopted a sequential research design in which bibliometric analysis serves as a methodologically sound foundation for subsequent in-depth investigations.

Unlike a traditional narrative literature review, the bibliometric approach enabled a more objective, systematic, and quantifiable analysis of the global body of literature. The literature review was deliberately planned as the second stage of the research process to mitigate risks of subjectivity, thematic narrowing, and selective inclusion of sources. Beginning with a bibliometric analysis allowed the authors to avoid the "bias of selection" commonly associated with narrative reviews (Snyder, 2019).

Using the R environment and the Bibliometrix package, the authors conducted a series of analyses, including citation analysis, co-word analysis, co-authorship network mapping, source analysis, and crucially, thematic clustering. This approach allowed for a comprehensive mapping of the knowledge structure and the temporal evolution of the field.

It is also important to emphasise that the time frame of the study (1987-2025) encompasses two rapidly evolving domains, artificial intelligence and marketing technologies. Both fields undergo constant technological, cognitive, and practical transformations, making manual tracking via literature review alone highly challenging, if not unfeasible. In this context, bibliometric tools enabled the authors to process and analyse hundreds of records simultaneously, providing the necessary scalability and precision required to explore such a dynamic research landscape (Donthu et al., 2021).

An essential factor justifying the use of bibliometrics in this study was its capacity to identify so-called thematic clusters, groups of publications linked by shared topics or methodological approaches that often signal the emergence of future research directions. The co-word analysis facilitated the identification of frequently co-occurring concepts, technologies, and research streams. This, in turn, allowed the authors to recognise not only leading topics but also research gaps that had been previously overlooked or marginally addressed (Aria & Cuccurullo, 2017; Massimo & Cuccurullo, 2017). The application of bibliometric analysis in research related to marketing and technology is well-established and has yielded significant insights, particularly in the fields of digital marketing, mobile technologies, and artificial intelligence in managerial contexts (De Luca et al., 2021; Thakur & Kushwaha, 2024).

In light of the early, dynamic, and multifaceted nature of the AI-MarTech convergence, bibliometrics constituted a critical and foundational method at this

Tab. 1. Search strategies for academic databases

Scientific search engine	Search phrases
Scopus	*TITLE-ABS-KEY (AI OR artificial intelligence) AND (marketing) AND (technology)*
Web of Science	*TS=(AI OR artificial intelligence) AND (marketing) AND (technology)*

stage of the research: it enabled an objective, scalable mapping of the literature corpus, reduced the risk of selection biases typical of narrative reviews, and captured the knowledge structure and its temporal evolution. The use of the Bibliometrix package (R) further allowed the identification of thematic clusters, dominant research streams, and research gaps that had hitherto been marginalised in the literature.

2.2. Inclusion and exclusion criteria

To ensure thematic relevance and analytical rigour, the following criteria were applied:

Inclusion criteria:

- Peer-reviewed research articles and literature reviews;
- Publications written in English;
- Articles published in any year, without time restriction;
- Articles indexed in the fields of business, management, or closely related areas;
- Explicit focus on artificial intelligence in the context of marketing technologies.

Exclusion criteria:

- Publications not directly related to AI or MarTech (off-topic);
- Non-English articles;
- Duplicates;
- Other publication types (e.g., book chapters, books, conceptual essays, workshop materials, student theses, editorials, or posters).

This methodologically grounded selection process ensured both the relevance and quality of the final dataset. By focusing on validated scholarly outputs from two high-impact databases, the authors assembled a coherent and representative corpus. This collection served as a reliable foundation for analysing trends, mapping the evolution of AI-MarTech research, and identifying emerging conceptual clusters.

3. Research results

3.1. Dataset and indicators

To ensure methodological consistency, Scopus and Web of Science databases were queried using standardised keyword sets and filtering protocols. The search was limited to peer-reviewed articles published in English and indexed in the fields of business, management, and social sciences. To identify the thematically most appropriate set of scholarly publications, the authors implemented a five-stage protocol for preparing and selecting the database for the bibliometric analysis. The protocol comprised the following stages (Fig. 1):

- Specification of article selection criteria;
- Curation of article datasets from Web of Science and Scopus;
- Preliminary analysis of both datasets based on author-supplied keywords;
- Decision regarding the selection of the database to be subjected to the main analysis;
- Main bibliometric analysis.

Preliminary analysis based on author-supplied keywords revealed that, although the Web of Science dataset was substantially larger (1,512 publications), only 3 % of its records contained the keyword “marketing”, whereas the share in Scopus exceeded 7 % in 449 publications. This pronounced disparity informed the decision to designate Scopus as the primary dataset for the subsequent bibliometric analysis. Following the preliminary comparison, the final corpus of 492 records was drawn from Scopus only (post-filtering), which we treat as the primary dataset for all subsequent analyses.

The final dataset consisted of 492 scientific publications published between 1987 and 2025, drawn from 278 unique sources (journals). The analysis confirmed a clear upward trend in scholarly interest: the average annual growth rate of publications during the study period was 7.39 %, which reflects the dynamic expansion of this interdisciplinary field (Small, 1999).

The dataset included contributions from 1,431 unique authors, of whom only 69 authored single-author papers, accounting for 4.82 % of the total. The average number of co-authors per article was 3.17, indicating a high degree of collaboration and the dominance of team-based knowledge production, particularly in technologically intensive domains, such as AI and marketing. Moreover, the share of international co-authorship reached 27.24 %, underscoring the global scope of the discourse (Glänzel & Schubert, 2004; Moed et al., 2004).

The average citation rate across the sample was 34.71 citations per document, signalling a high level of academic impact. The average document age was 3.35 years, which confirms the field’s orientation towards recent developments, typical for disciplines shaped by rapid technological innovation (Bornmann & Daniel, 2008).

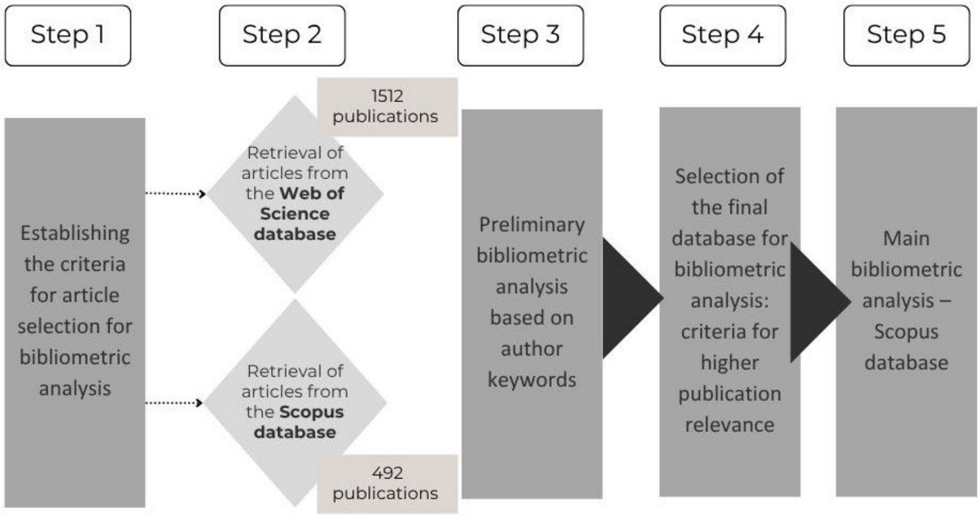

Fig. 1. Stages of preparation and selection of the database for bibliometric analysis

Tab. 2. Author keyword analysis in the Web of Science and Scopus databases: a preliminary assessment underpinning the selection of the database for the final bibliometric analysis

Web of Science database

Author keywords	Number of publications
artificial intelligence	456
technology	69
ai	65
artificial intelligence (ai)	56
marketing	48
machine learning	45
innovation	42
artificial	36
intelligence	32
generative ai	31
digital marketing	25
digitalization	25
anthropomorphism	24
chatgpt	23
trust	22
business	20
chatbot	20
customer experience	20
technology adoption	20
blockchain	18
performance	18
big data	17
service	17
chatbots	16
digital	16

Scopus database

Author keywords	Number of publications
artificial intelligence	233
marketing	56
digital marketing	33
machine learning	30
ai	29
technology	26
artificial intelligence (ai)	21
big data	19
chatgpt	15
internet of things	14
innovation	12
social media	12
technology adoption	12
tourism	12
generative ai	11
generative artificial intelligence	11
covid-19	10
customer experience	10
digital transformation	10
adoption	9
chatbots	9
chatbot	8
deep learning	8
information technology	8
retailing	8

Source: author’s elaboration on the basis of R software.

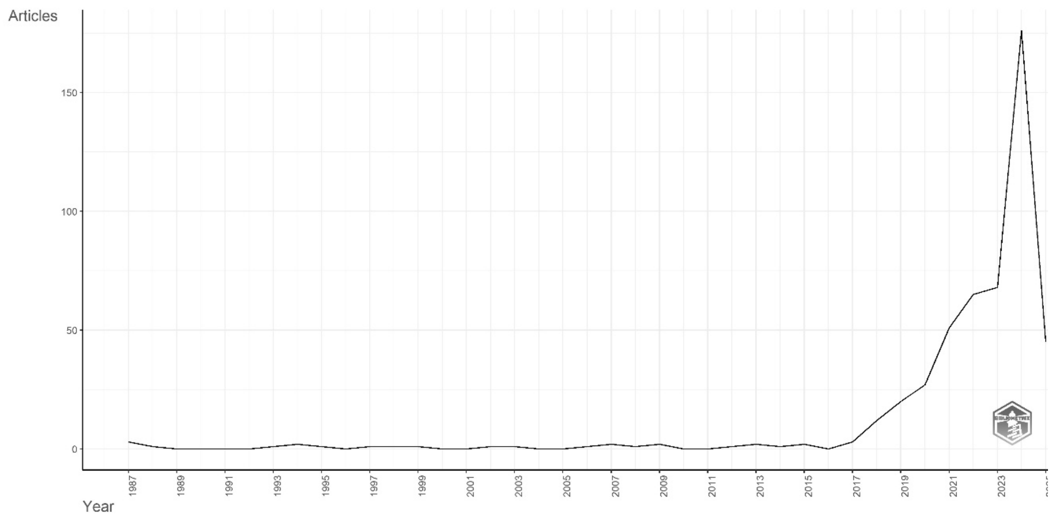

Fig. 2. Distribution of scientific publications in the thematic area of AI and marketing technologies in 1987-2025

Source: author's elaboration on the basis of R software.

In terms of thematic diversity, the corpus included 1,685 unique keywords, reflecting the complexity and interdisciplinary nature of the AI-MarTech research space. The dataset also comprised 31,817 cited references, indicating a dense citation network and robust knowledge base - key markers of maturity in an academic field (Leydesdorff, 2001).

Together, these indicators confirm that AI-driven marketing technologies constitute a rapidly evolving, globally relevant, and theoretically rich domain. The scope and structure of the data justify the use of advanced bibliometric mapping to uncover trends, influential contributors, and underexplored areas that warrant further scholarly attention. In particular, the data reveal a significant surge in publication activity during the period 2015-2025, with an average growth rate of 36.53 %, more than four times the rate observed across the entire study window. This sharp upward trend is illustrated in Fig. 2, which highlights a rapid acceleration of scholarly interest in AI-driven marketing technologies.

3.2. Thematic clusters and network analysis

3.2.1. Primary specification (Analysis 1)

The authors conducted a qualitative interpretation of clusters based on a clearly specified, replicable analytical pipeline. First, clusters were identified in Biblioshiny (Bibliometrix) using Clustering by Coupling with the following settings: Unit of Analysis = Documents; Coupling measured by = References (bibliographic coupling); Impact measure = Local Citation Score (LCS); Cluster labelling by = Index Keywords; Number of Units = 250; Min Cluster Freq. = 5; Labels per cluster = 3; Label size = 0.3. Next, in the qualitative stage, the authors examined for each cluster: (i) the Index Keywords label profile with conf % shares (as the cluster's semantic fingerprint), (ii) the freq/centrality/impact (LCS) metrics describing scale and network embedding, and (iii) the position within Callon's quadrants (motor/basic/niche/emerging) derived from the thematic map (centrality-density). The interpretation thus combined the content signature (dominant keywords) with structural embedding (centrality) and internal maturity (density/impact), enabling the authors to identify cluster roles (e.g., motor vs niche), their likely developmental trajectories (movement towards higher centrality via links to outcome metrics), and integration gaps (areas of high density but low centrality).

3.2.2. Comparative specification (Analysis 2)

For triangulation, the authors replicated the procedure with an alternative yet comparable configuration: Unit of Analysis = Documents; Coupling measured by = References; Impact measure = Global Citation Score (GCS); Cluster labelling by = Authors' keywords; Number of Units = 250; Min Cluster Freq. = 5; Labels per cluster = 3; Label size = 0.3. Holding the unit of analysis, coupling method, and thresholds constant while switching the impact metric (LCS -> GCS) and the labelling source (Index Keywords ->

Authors' keywords) provides a complementary perspective: the LCS/Index-Keywords view emphasises corpus-internal influence and algorithmically derived index terms, whereas the GCS/Authors'-keywords view foregrounds globally cited contributions and author-intended terminology. The side-by-side results improve interpretive robustness by revealing where conclusions are stable across specifications and where topic prominence is sensitive to impact and labelling choices.

To identify the core research themes and their interconnections within the AI-MarTech domain, a co-word analysis was conducted based on author keywords and index keywords fields. Using Biblioshiny's clustering algorithms, the study generated a co-occurrence network and performed Callon's centrality and density analysis to classify themes according to their strategic relevance and internal coherence.

Across the two specifications, the field's structure is stable: the AI-marketing core remains the most central cluster (Cluster 1: innovation 66.7 %, marketing 16.7 %, AI 9.5 %; n=111, centrality=0.496, impact=2.848 in LCS), with adoption (Cluster 2: technology adoption 62.5 %, AI 47.6 %, marketing 33.3 %; n=92, centrality=0.347, impact=1.458 LCS / 4.409 GCS) and market applications (Cluster 3: commerce 54.5 %, AI 23.8 %, marketing 27.8 %; n=36, centrality=0.306, impact=1.269 LCS / 2.604 GCS) forming the main flanking streams. What changes with configuration is perceived impact and labelling: using GCS + Authors' keywords amplifies the impact of adoption and digital/commerce (global resonance) and surfaces precise emergent terms (e.g., virtual influencers), whereas LCS + Index Keywords emphasise influence within the analysed corpus and aggregates emergents under broader notions (e.g., perception). Within this backbone, the thematic map delineates five clusters in the centrality-density space: besides the core (Cluster 1), Cluster 2 captures adoption dynamics, Cluster 3 operationalises value in commerce/digital marketing, and two smaller clusters mark early-stage lines of inquiry Cluster 4 centred on perception (75 %; n=7, centrality=0.189, impact=1) and Cluster 5 on generative AI/ChatGPT (n=4, centrality≈0.18-0.19, impact=1 LCS / 2.518 GCS). Notably, generative AI/ChatGPT remains low in centrality (an emerging theme) yet shows faster citation uptake under GCS, while the human-centred strand may appear as "perception" in Index-based labelling or as "virtual influencers/advertising effects" when Authors' keywords are used, underscoring how labelling sources shape the visibility of nascent topics (Tables 3-4).

The expanding corpus of publications on AI and MarTech unequivocally evidences intensifying scholarly interest in this domain. The five identified thematic clusters delineate an integrated knowledge axis, from innovation (Cluster 1), through adoption (Cluster 2), to implementation outcomes (Cluster 3) of AI in marketing. This core is complemented by two relatively nascent areas: human-centred mediators (Cluster 4) and a generative accelerator (Cluster 5). The practical implications are already clear: organisations deploying AI in marketing should develop technology maturity models, invest in governance and explainable AI (XAI), evaluate effects experimentally (A/B and quasi-experimental designs), and systematically report ROI and associated risks. Taken together, this configuration of thematic clusters opens a rich and diversified research agenda for both scholarship and managerial practice.

The table below synthesises the co-word analysis of the AI-MarTech literature, delineating five the-

Tab. 3. Clusters according to bibliographic links. Publications from 1987-2025 - primary specification (Analysis 1)

Description	Cluster	Number of publications	Centrality	Impact
marketing - conf 16.7 % artificial intelligence - conf 9.5 % innovation - conf 66.7%	1	111	0.496	2.848
artificial intelligence - conf 47.6 % marketing - conf 33.3 % technology adoption - conf 62.5 %	2	92	0.347	1.458
commerce - conf 54.5 % artificial intelligence - conf 23.8 % marketing - conf 27.8 %	3	36	0.306	1.269
artificial intelligence - conf 19 % marketing - conf 16.7 % perception - conf 75 %	4	7	0.189	1
chatgpt - conf 33.3 % generative artificial intelligence - conf 42.9 % ai - conf 13.3 %	5	4	0.190	1

Source: author's elaboration on the basis of R software.

Tab. 4. Clusters according to bibliographic links. Publications from 1987-2025 - comparative specification (Analysis 2)

Description	Cluster	Number of publications	Centrality	Impact
artificial intelligence - conf 36.4 % marketing - conf 22.9 % technology adoption - conf 87.5 %	1	92	0.347	4.409
virtual influencers - conf 100 % virtual influencer - conf 100 % advertising effects - conf 100 %	2	7	0.189	2.575
artificial intelligence - conf 14.3 % digital marketing - conf 62.5 % marketing - conf 22.9 %	3	36	0.306	2.604
artificial intelligence - conf 47.9 % marketing - conf 51.4 % technology - conf 55.6 %	4	111	0.496	2.661
chatgpt - conf 33.3 % generative artificial intelligence - conf 42.9 % ai - conf 13.3 %	5	4	0.183	2.518

Source: author's elaboration on the basis of R software.

matic clusters with their size (n), centrality, impact, and functional role in the thematic network. Cluster 1 functions as a motor theme, integrating innovation, AI applications, and marketing outcomes, and providing the conceptual-methodological scaffolding for the field. Cluster 2 constitutes a basic theme around technology adoption, linking sources of innovation (C1) to market outcomes (C3), while being strongly moderated by human-centred factors captured in Cluster 4 (trust, usability, and transparency). Cluster 3 reflects the operationalisation of value in commerce (recommendation, omnichannel, and conversational commerce); its high conceptual centrality indicates a transversal, integrating role and a trajectory towards motor-theme status. Cluster 4 represents a niche yet strategically important human-centred perspective that moderates adoption-outcome relationships. Cluster 5 captures the emerging generative-AI stream (LLMs (Large Language Models)/ChatGPT), acting as an accelerator for C1-C3 and elevating quality, safety, and compliance requirements associated with C4. Together, the clusters chart an innovation, adoption and outcomes pathway, with human factors and generative AI shaping its pace and governance (Table 5).

The thematic classification confirms that while core topics such as AI adoption and marketing innovation are well-established, important areas related to human-centred AI, emotional engagement, and ethical challenges remain underexplored. These findings support calls for a broader, more integrated research agenda that incorporates both technological and humanistic dimensions of AI implementation in marketing.

Further in-depth analysis of the thematic map, in relation to four areas: motor themes, basic themes, niche themes, and emerging or declining topics, allowed the authors to classify key concepts according to their importance in the structure of the discipline (centrality) and the degree of development (density).

- The data presented in the thematic map (Fig. 3), combined with the ranking analysis of Callon's centrality and density, allow for a more precise assessment of the importance of key concepts in the knowledge structure in the area of AI and marketing technologies. The highest centrality is achieved by the concept of commerce (centrality = 17.992; rank 11), which confirms its key role as a driving topic - well-developed and strongly related to other research areas. Similarly, high density (111.435; rank 10) indicates the intensive internal development of this topic. This is a surprising phenomenon, because in the importance of clusters, the concept of commerce appeared only in the 3rd thematic cluster - primary specification. The concept of artificial intelligence also holds a high position, which achieves a centrality of 12.943 (rank 10) and a density of 63.248 (rank 3), which confirms its role as a basic theme, i.e., strongly present in the structure but still being developed conceptually.
- In turn, sustainable development is characterised by a significantly lower centrality (8.695; rank 9) with a very high density (111.239; rank 9), which classifies it as a niche topic - well-developed, but with a limited integrative role in the knowledge system. Economic and social effects (centrality =

Tab. 5. Characteristics and significance of thematic clusters - based on the primary specification (Analysis 1)

Cluster	Main themes	N	Centrality	Impact	Profile and significance	Role and linkages	Stage and trajectories
1	marketing - conf 16.7 % artificial intelligence - conf 9.5 % innovation - conf 66.7 %	111	0.496	2.848	Largest, nodal cluster integrating the field's language: from innovation to AI applications to marketing outcomes; motor theme providing conceptual and methodological scaffolding for other streams.	Strong coupling with C2 (adoption) and C3 (commerce): innovation triggers implementation processes and materialises in market outcomes.	Mature, high-impact; shift towards platformisation and agentic systems (AI agents), standardisation of ROI metrics, governance and regulatory compliance.
2	artificial intelligence - conf 47.6 % marketing - conf 33.3 % technology adoption - conf 62.5 %	92	0.347	1.458	Organisational, behavioural stream: competencies, technological readiness, process fit, perceived value and risk.	Basic theme linking C1 (innovation sources) to C3 (outcomes); strongly moderated by C4 (trust, usability, transparency).	Consolidating; development of maturity models for AI adoption, effect measurement at process/team level; evidence-based adoption (A/B, quasi-experiments), change management.
3	commerce - conf 54.5 % artificial intelligence - conf 23.8 % marketing - conf 27.8 %	36	0.306	1.269	Market applications: recommendations, omnichannel, conversational commerce, retail media, path-to-purchase optimisation.	The concept "commerce" exhibits the highest centrality and high density at the concept-map level -> transversal integrator across clusters.	Moving towards motor theme; expansion of conversational commerce (LLM, semantic search, advisor agents), integration with supply chain and dynamic pricing, cross-channel attribution, privacy and compliance.
4	artificial intelligence - conf 19 % marketing - conf 16.7 % perception - conf 75 %	7	0.189	1	Human-centred perspective: attitudes, trust, acceptance, usability, emotion, ethics, AI disclosure.	Niche moderator of the C2 -> C3 relationship (adoption -> outcomes).	Early but high growth potential: XAI, disclosure, anthropomorphism, user control, cultural differences; longitudinal studies of emotion and trust.
5	chatgpt - conf 33.3 % generative artificial intelligence - conf 42.9 % ai - conf 13.3 %	4	0.19	1	Most emerging technical, methodological stream: LLMs, content generation, new interaction protocols (prompting), applications in marketing and commerce.	Accelerator for C1-C3; elevates the salience of C4 (quality, safety, ethics).	Transition from chatbots to agentic systems; multimodality; automation of creative work and campaign optimisation; quality-evaluation frameworks (guardrails, hallucinations, compliance).

1.458; density = 111.574), ranking only 5th in terms of centrality, despite its very high internal development (rank 11 in terms of density).

- According to the data, machine learning (centrality 6.696; density 66.865) and decision-making (centrality 4.894; density 89.672) should be considered as intermediate topics - developing and increasingly present, but not yet dominant. Customer service (centrality 1.604) also belongs to this group, although its relatively low cluster frequency (14) may indicate a limited number of studies.
- Among the emerging or marginal topics are concepts such as adversarial machine learning, delivery of health care, ecotourism and speech recognition - all characterised by zero centrality

Tab. 6. Key concepts and their importance in the research area - tabular presentation

Key concept	Callon's centrality	Callon density	Centrality ranking	Density ranking	Cluster frequency
commerce	17.992	111.435	11	10	241
artificial intelligence	12.943	63.248	10	3	263
Sustainable development	8.695	111.239	9	9	41
machine learning	6.696	66.865	8	4	27
decision making	4.894	89.672	7	7	86
customer service	1.604	87.5	6	6	14
economic and social effects	1.458	111.574	5	11	21
adversarial machine learning	0	50	2.5	1.5	2
delivery of health care	0	75	2.5	5	4
ecotourism	0	108.333	2.5	8	12
speech recognition	0	50	2.5	1.5	2

Source: author's elaboration on the basis of R software.

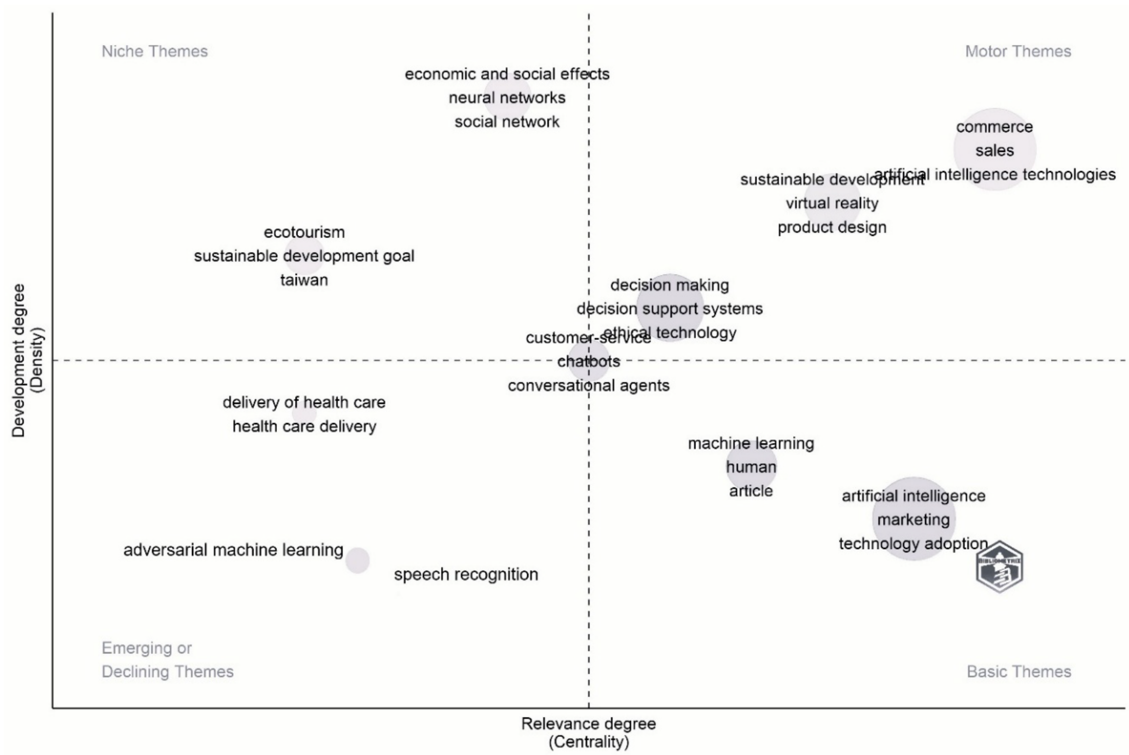

Fig. 3. Key concepts and their importance in the research area - tabular presentation

Source: author's elaboration on the basis of R software.

and low density, but appearing as new themes in the analysed literature (Table 6).

As an extension of the cluster-level results, the keyword analysis interpreted through Callon's centrality and density provides a qualitative lens on how specific concepts shape knowledge development in AI-MarTech and where they may steer future inquiry. By assessing each keyword's current network position (integrative relevance) and internal development (cohesion), the authors infer its prospective impact trajectory and the most promising linkages to outcome-oriented streams. The table below summarises these insights, reporting the metrics and the authors' succinct inferences ("Authors posit that") to indicate how research organised around each keyword is likely to evolve (Table 7).

Tab. 7. Keywords in the thematics clusters analysis, the author's perspective in the AI-MarTech domain

Keyword	Segment (Callon)	Current placement on the thematic map	Authors posit that
Commerce	Motor	Already a motor keyword; it bridges disparate themes and anchors outcome metrics.	it will retain its integrative role, with future studies deepening causal links to adoption and decision processes and standardising ROI - Return on Investment /attribution measures, thereby further increasing centrality.
Artificial intelligence	Basic	An infrastructural, corpus-wide keyword that still advances conceptually.	greater conceptual specification and typology building, coupled with tighter links to governance and outcomes, will raise internal cohesion (density) and consolidate its basic status.
Sustainable development	Niche	Well-developed locally, yet weakly integrative at the system level.	centrality will increase if sustainability frames are operationalised in adoption pathways and outcome metrics (e.g., carbon footprint of campaigns, eco-ROI - Return on Investment).
Economic and social effects	Niche	Locally mature but peripheral; measurement is uneven.	standardising indicator panels and deploying quasi-experimental designs will elevate centrality by connecting effects to the adoption-decision-commerce chain.
Machine learning	Intermediate	Growing and methodologically mature, but not yet dominant.	application-oriented studies (recommendation, personalisation) that tie ML interventions to decision processes and commerce outcomes will increase network centrality.
Decision-making	Intermediate	Internally developed; currently moderate connectivity.	it will strengthen as a mediating node as studies model mediation/moderation along the adoption-decision-commerce pathway.
Customer service	Intermediate (narrow)	Coherent but limited in scale and connectivity.	centrality will rise if embedded in omnichannel and conversational commerce and aligned with outcome metrics (NPS - Net Promoter Score, CLV - Customer Lifetime Value, conversion).
Adversarial machine learning	Emerging/Marginal	Early-stage and isolated within AI-MarTech.	it will gain traction once positioned within marketing risk and governance use-cases, including model robustness assessments in campaigns and personalisation.
Delivery of health care	Emerging/Marginal	Sector-specific and peripheral to MarTech.	it is likely to remain peripheral unless transferability tests (e.g., patient journey - customer journey) demonstrate relevance to mainstream AI-MarTech outcomes.
Ecotourism	Emerging/Marginal (locally consolidated)	Consolidated locally but disconnected from the core network.	centrality will increase only if insights are translated into mainstream marketing metrics and adoption routes.
Speech recognition	Emerging/Marginal	Early-stage; limited links to outcomes.	it may move towards the core as voice/multimodal commerce matures and is explicitly tied to measurable outcomes (conversions, retention).

3.3. Authors of publications and research centres

The conducted analysis of authors and research centres highlights the current situation regarding dominant researchers, universities and regions specialising in the analysed scope, i.e., AI and marketing technologies.

Assessing the activity of the authors, the leaders in terms of the number of articles are Dwivedi and Kumar. Each of them published five articles in the analysed period. They were followed by two researchers, Kim and Zhang, with four publications. The next large group consists of researchers with three articles and varying intensity of their citations (Table 8).

Tab. 8. Author productivity in 2019-2025

Author	Year	Frequency	Total citations	Total citations /year
AW EC-X	2024	1	11	5.5
AW EC-X	2025	2	0	0
BILGIHAN A	2020	1	18	3
BILGIHAN A	2024	2	21	10.5
BUHALIS D	2019	1	533	76.143
BUHALIS D	2023	1	1819	606.333
BUHALIS D	2024	1	11	2.5
DATA COSTA RL	2022	2	10	2.5
DATA COSTA RL	2023	1	3	1
DIAS A	2022	2	10	5.5
DIAS A	2023	1	3	1
DWIVEDI YK	2021	1	128	25.6
DWIVEDI YK	2023	2	1881	627
DWIVEDI YK	2024	1	11	5.5
DWIVEDI YK	2025	1	0	0
GONÇALVES R	2022	2	10	2.5
GONÇALVES R	2023	1	3	1
WHO M	2022	1	40	10
WHO M	2024	3	5	2.5
KUMAR V	2019	1	406	58
KUMAR V	2021	1	239	47.8
KUMAR V	2024	3	75	37.5
ZHANG J	2021	1	62	12.4
ZHANG J	2023	1	5	1.667
ZHANG J	2024	2	14	7

Source: author's elaboration on the basis of R software.

The analysis of authors' citations in the context of years of publication and the number of works published annually does not show any significant differences between the authors studied. Significant differentiation occurs at the level of the number of citations and clearly indicates the presence of authors with a dominant citation position and those whose scientific influence is relatively low.

The most influential authors in terms of citations work scientifically at universities in the UK. They are Buhalis, Dwivedi, and Mogaji. Dimitrios Buhalis, professor of marketing, strategy and innovation at Bournemouth University in the UK, has the highest number of citations (TC = 2363). His works are very popular in the scientific community, despite a lower Hirsch index (3). Yogesh K. Dwivedi, professor of digital marketing and innovation at Swansea University in the UK (h_index = 4, g_index = 5, m_index = 0.8, TC = 2020), started publishing in 2021 and has already obtained an impressive number of citations. His research topics touch, among others, on contemporary marketing challenges in the area of social media and the metaverse. Dr Emanuel Mogaji works at the University of Keele in the UK (TC = 2054) and works in marketing. Despite his relatively low H-index (3), his publications have a high number of citations, which suggests that he has several very influential articles (Table 8-9).

Another interesting aspect in the context of the authors is their willingness to cooperate with partners outside their own country. Considering the map of international cooperation of all the authors, differences can be observed between countries in terms of openness to conducting research outside their coun-

Tab. 9. Analysis of the most influential authors of research and scientific publications

Author	h_index	g_index	m_index	Total Citations (TC)	Number of publications (NP)	Year of publication commencement
KUMAR V	5	5	0.714	720	5	2019
DWIVEDI YK	4	5	0.8	2020	5	2021
BUHALIS D	3	3	0.429	2363	3	2019
DA COSTA RL	3	3	0.75	13	3	2022
DIAS Á	3	3	0.75	13	3	2022
GONÇALVES R	3	3	0.75	13	3	2022
LEE J	3	3	0.6	57	3	2021
MOGAJI E	3	3	0.6	2054	3	2021
PEREIRA L	3	3	0.75	13	3	2022
PUNTONI S	3	3	0.6	535	3	2021

Source: author's elaboration on the basis of R software.

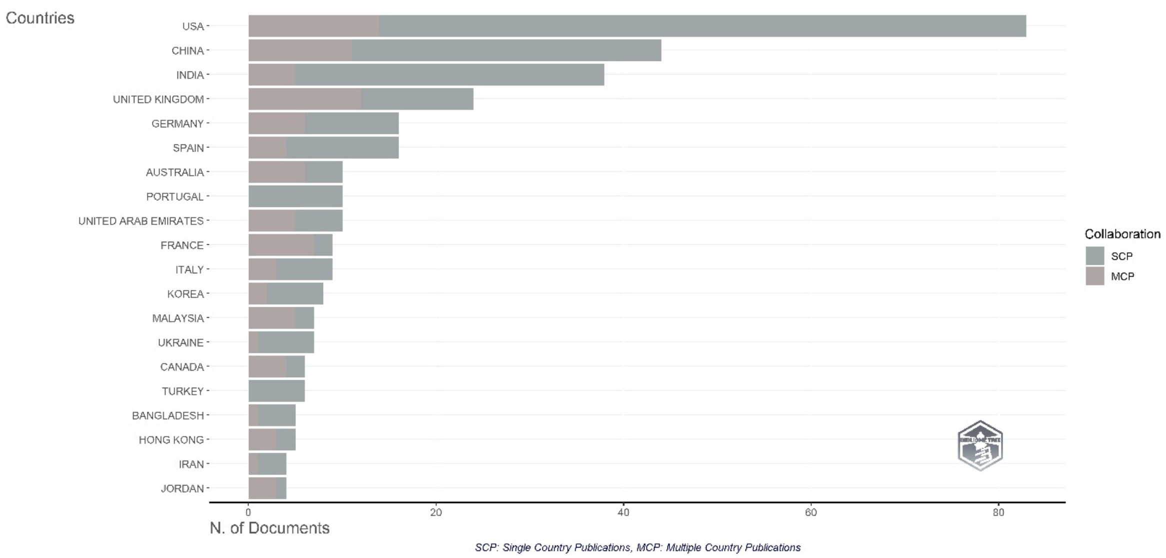

Fig. 4. Map of the authors' international cooperation, the examined period 1987-2025

Source: author's elaboration on the basis of R software.

tries. The greatest openness to international cooperation is shown by research centres from Great Britain, Australia, France, Canada, Malaysia, and Jordan. The remaining centres, especially the most productive ones from the United States, China, and India, remain largely at the level of their domestic research, limiting scientific cooperation to their region (Fig. 4).

3.4. Leading research institutions and university contributions

Although the most influential authors of publications are researchers from Great Britain, the largest number of publications per academic centre comes from Australian universities. The five most active universities in terms of publications are: Queensland University of Technology in Australia (14 publications), UCSI University in Malaysia (10 publications), Swansea University in Great Britain (9 publications), The Hong Kong Polytechnic University (9 publications) and Auckland University of Technology in New Zealand (8 publications) (Table 10).

When analysing the specificity of scientific research conducted by the five top-mentioned universities, it is worth emphasising that all of these universities have a strong research specialisation in

Tab. 10. University centres and their productivity in 1987-2025

Lp.	University centre	Articles
1	QUEENSLAND UNIVERSITY OF TECHNOLOGY	14
2	UCSI UNIVERSITY	10
3	SWANSEA UNIVERSITY	9
4	THE HONG KONG POLYTECHNIC UNIVERSITY	9
5	AUCKLAND UNIVERSITY OF TECHNOLOGY	8
6	GRIFFITH UNIVERSITY	8
7	INSTITUTO UNIVERSITÁRIO DE LISBOA	8
8	NORTHEASTERN UNIVERSITY	8
9	UNIVERSITY OF GRANADA	8
10	KHMELNYTSKYI NATIONAL UNIVERSITY	7
11	NORTH CHINA UNIVERSITY OF WATER RESOURCES AND ELECTRIC POWER	7
12	UNIVERSITY OF NORTH TEXAS	7
13	UNIVERSITY OF ZILINA	7
14	YONSEI UNIVERSITY	7
15	AARHUS UNIVERSITY	6
16	FLORIDA STATE UNIVERSITY	6
17	KOREA UNIVERSITY	6
18	MOHAMMED VI POLYTECHNIC UNIVERSITY	6
19	NATIONAL INSTITUTE OF INDUSTRIAL ENGINEERING (NITIE)	6
20	SYMBIOSIS INTERNATIONAL (DEEMED UNIVERSITY)	6
21	TRANSILVANIA UNIVERSITY OF BRAȘOV	6
22	XI'AN UNIVERSITY OF SCIENCE AND TECHNOLOGY	6
23	JINAN UNIVERSITY	5
24	NANYANG TECHNOLOGICAL UNIVERSITY	5
25	NATIONAL TAICHUNG UNIVERSITY OF SCIENCE AND TECHNOLOGY	5

Source: author's elaboration on the basis of R software.

each of the three areas, i.e., AI, management, and marketing.

Queensland University of Technology has a strong research background in data science, AI, and digital marketing. The university is known for its practical and implementation approach - exploring the application of AI in real-world marketing scenarios. The Social Marketing (Research Group) aims to develop and integrate marketing concepts with other approaches, including in relation to the digital world, to drive behavioural change and social transformation that benefits consumers, society and the planet (source: https://research.qut.edu.au/social-marketing-research-group/).

UCSI University in Malaysia actively collaborates with government programmes to develop AI research. UCSI University has partnered with RICOH Malaysia to establish an IT research and development lab equipped with modern equipment. This lab is intended for postgraduate and final year IT students, which promotes AI research and digital innovation (source: https://www.ucsiuniversity.edu.my/ucsi-university-and-ricoh-malaysia-establish-partnership-to-create-research-and-development-lab).

When analysing the reasons for the high productivity of Swansea University in the UK, several factors can be seen that contribute to this situation. First, the university collaborates with renowned researchers, including Professor Yogesh Dwivedi, who, as previously mentioned in the authors' analysis, is an influential authority on scientific publications in the area of AI in marketing. The university develops research topics in the field of digital consumer behaviour, MarTech, and the digital transformation of organisations. The university has a research unit, the Centre for Digital Economy, which combines research on AI, e-commerce, and management.

The Hong Kong Polytechnic University is one of the most active universities in this country, developing programmes in business intelligence, AI, e-commerce, and marketing management. Hong Kong, as a key technology hub, supports and finances cooperation with universities. An additional favourable aspect for the development of applied research and publications is the functioning of a large network of startups with which this university cooperates.

The last university in the top five is the Auckland University of Technology from New Zealand, which conducts a lot of research around AI. It focuses on the ethical and social aspects of technology development. The university promotes a human-centred approach to AI - especially in the context of the impact of technology on consumer behaviour. It can be assumed that this is one of the future research trends, considering the above-described thematic clusters.

3.5. Geographic analysis of publication counts and scientific impact in the field of AI and marketing technologies

The analysis of the number of scientific publications by country shows the dominant position of the United States (275 publications), which has the longest and most developed research and business ecosystem supporting innovations in the field of artificial intelligence and marketing technologies. The next positions are occupied by India (150) and China (147) - countries that are dynamically developing the digital sector, supported by both government policies and the growing number of specialists in the field of data science and MarTech. Great Britain (86) also demonstrates high scientific activity, benefiting from strong academic centres and numerous international partnerships.

Complementing the quantitative analysis, the breakdown reveals interesting differences in the scientific impact of publications, measured by the number of citations per article on average. The highest average number of citations per article is achieved by the United Kingdom (137.9), which indicates high quality and influence of a smaller number of publications. In comparison, the USA - although leading in the number of documents - achieves an average of 33.1 citations per article, which may indicate a wider range of quality or a greater share of publications with an applied character. High average citations are also recorded by France (92.4), Australia (62.5), Switzerland (62.2), and Ireland (65.0), which confirms their specialisation in niche but highly valued research topics.

In turn, China (18.0), the United Arab Emirates (16.1), and India (35.9) are characterised by a lower average citation rate, despite a large number of publications, which may indicate a greater focus on quantity than on international scientific impact. Ukraine (7.1) and Bangladesh (8.4) draw particular attention - despite high activity in the number of documents, their impact measured by citations is relatively low.

Poland, although not among the top publications, ranks 17th out of 72 countries (35 positions listed in Table 11), and appears in the ranking with 34 citations and an average of 8.5 per article, which may indicate a growing, but still limited, involvement in the global academic debate on AI and MarTech.

The findings suggest that the number of publications does not always correlate with their impact. Countries such as the UK, France and Australia show that strategic and well-grounded research can be more important than mass production of content. In addition, the data underscore the importance of the quality of scientific collaboration, the reputation of research centres and the specificity of the topics addressed by researchers (Table 11).

Interestingly, while the United States dominates in total publication volume, it is the United Kingdom that ranks highest in average citation impact per article. This suggests a strategic focus on theoretical contributions and global relevance, despite producing fewer total documents.

The geographic distribution of institutions also reflects the global nature of AI-MarTech research, with notable activity across Europe, Asia-Pacific, and North America. Furthermore, several smaller countries, such as the Netherlands, Belgium, and Singapore, exhibited disproportionately high citation impact, often attributable to international research collaborations and interdisciplinary projects.

Taken together, these findings highlight the critical role of a small number of globally engaged universities in advancing the AI-MarTech research agenda. Their influence is amplified by strong international networks and a clear alignment with strategic research

Tab. 11. Number of publications and citations per country

Lp.	Country	Number of publications
1	USA	275
2	INDIA	150
3	CHINA	147
4	UK	86
5	SPAIN	57
6	UKRAINE	55
7	AUSTRALIA	51
8	ITALY	47
9	PORTUGAL	43
10	GERMANY	39
11	SOUTH KOREA	33
12	FRANCE	31
13	MALAYSIA	30
14	JORDAN	24
15	NEW ZEALAND	23
16	ROMANIA	23
17	POLAND	20
18	FINLAND	18
19	SAUDI ARABIA	18
20	UNITED ARAB EMIRATES	18
21	CANADA	17
22	INDONESIA	16
23	TURKEY	16
24	SINGAPORE	15
25	BANGLADESH	13
26	IRAN	13
27	SLOVAKIA	12
28	GREECE	11
29	MEXICO	10
30	SWITZERLAND	10
31	ISRAEL	9
32	DENMARK	8
33	NETHERLANDS	8
34	SWEDEN	8
35	CROATIA	7

Lp.	Country	Total citations	Citations per article
1	UNITED KINGDOM	3 309	137.88
2	USA	2 748	33.11
3	INDIA	1 366	35.95
4	SPAIN	903	56.44
5	FRANCE	832	92.44
6	GERMANY	827	51.69
7	CHINA	792	18.00
8	AUSTRALIA	625	62.50
9	PORTUGAL	381	38.10
10	KOREA	316	39.50
11	ITALY	260	28.89
12	SWITZERLAND	249	62.25
13	MALAYSIA	229	32.71
14	HONG KONG	221	44.20
15	CANADA	202	33.67
16	FINLAND	179	59.67
17	AUSTRIA	95	47.50
18	IRELAND	65	65.00
19	SWEDEN	64	32.00
20	SINGAPORE	63	15.75
21	MEXICO	61	15.25
22	IRAN	58	14.50
23	NETHERLANDS	58	14.50
24	LITHUANIA	57	28.50
25	DENMARK	53	26.50
26	UKRAINE	50	7.14
27	JAPAN	42	42.00
28	BANGLADESH	42	8.40
29	ROMANIA	41	13.67
30	POLAND	34	8.50
31	NEW ZEALAND	27	6.75
32	TURKEY	20	3.33
33	MOROCCO	17	17.00
34	SRI LANKA	11	5.50
35	GEORGIA	10	3.33

Source: author's elaboration on the basis of R software.

priorities in marketing, data science, and digital innovation.

3.6. Analysis of the most influential global publications

The analysis of documents with the highest citations indicates a clear dominance of articles by Dwivedi, who achieved 1,819 total citations in 2023 and an impressive average of 606.33 citations per year, making it both the most influential and the fastest gaining recognition of scientific texts in the area of AI and marketing technologies. The articles by Hoyer (article from 2020), Buhalis (from 2019), and Wamba-Taguimdje (from 2020) also stand out with a high number of citations - all exceeding the threshold of 500 citations, which proves their significant contribution to the development of literature. The publication by Puntoni (2021) also draws special attention, with a total number of 496 citations, recording an average of 99.2 citations per year, confirming the relevance and practical importance of the subject matter.

The annual citation breakdown clearly shows which publications have gained the fastest resonance in the scientific community, making them an important reference for further research. This indicates the dynamic development of the research field after 2020, especially in the context of the growing importance of artificial intelligence in digital marketing, building customer experiences and the transformation of management models. Moreover, publications from 2019-2021, despite their relatively short time in the scientific circulation, achieve comparable or higher citation rates than older works, which confirms the acceleration of researchers' interest in AI and MarTech in recent years (Table 12).

Tab. 12. Analysis of the Top 25 influential publications based on the number of citations

LP.	Authors / Articles	Total citations	Citations/year	Normalised citation count
1	DWIVEDI YK, 2023, INT J INF MANAGE	1819	606.33	42.30
2	HOYER WD, 2020, J INTERACT MARK	542	90.33	4.67
3	BUHALIS D, 2019, J TRAVEL TOUR MARK	533	76.14	4.67
4	WAMBA-TAGUIMDJE SL, 2020, BUS PROCESS MANAGE J	502	83.67	4.33
5	PUNTONI S, 2021, J MARK	496	99.20	6.39
6	BELANCHE D, 2019, IND MANAGE DATA SYS	419	59.86	3.67
7	KUMAR V, 2019, CALIF MANAGE REV	406	58.00	3.56
8	VERMA S, 2021, INT J INF MANAG DATA INSIGHTS	377	75.40	4.86
9	ALMEIDA F, 2020, IEEE ENG MANAGE REV	326	54.33	2.81
10	PORIA S, 2014, KNOWL BASED SYST	275	22.92	1.00
11	STEINHOFF L, 2019, J ACAD MARK SCI	252	36.00	2.21
12	KUMAR V, 2021, J BUS RES	239	47.80	3.08
13	RUST RT, 2020, INT J RES MARK	217	36.17	1.87
14	QUACH S, 2022, J ACAD MARK SCI	211	52.75	5.67
15	PILLAI R, 2020, BENCHMARKING	208	34.67	1.79
16	YIGITCANLAR T, 2020, SUSTAINABILITY	187	31.17	1.67
17	SAURA JR, 2021, IND MARK MANAGE	172	34.40	2.22
18	CHINTALAPATI S, 2022, INT J MARK RES	171	42.75	4.59
19	CLOSS DJ, 2008, J OPER MANAGE	169	wrz.39	1.00
20	HAMILTON R, 2021, J MARK	167	33.40	2.15
21	SAMALA N, 2022, J TOUR FUTUR	161	40.25	4.33
22	DE BELLIS E, 2020, J RETAIL	156	26.00	1.34
23	MANSER PAYNE EH, 2021, J RES INTERACT MARK	155	31.00	2.00
24	MANSER PAYNE EH, 2021, J RES INTERACT MARK	137	27.40	1.77
25	YIGITCANLAR T, 2020, J OPEN INNOV: TECHNOL MARK COMPLEX	134	22.33	1.15

Source: author's elaboration on the basis of R software.

3.7. Cited source analysis by year of publication (RPYS)

Results of the spectroscopy analysis of the publication years of the cited sources (Reference Publication Year Spectroscopy) clearly indicate that research in the area of artificial intelligence and marketing technologies is based primarily on current scientific literature. The vast majority of cited works come from the period 2000-2022, with a particularly intensive increase in citations observed in the years 2015-2021. This means that the theoretical foundations and the development of tools and methods in this field have been dynamically shaped in the last decade.

Analysis of deviations from the five-year median of citations (light grey line in Fig. 5) reveals significant increases in the years 2016-2019, which can be interpreted as moments of publication of breakthrough works, in the field of artificial intelligence (e.g., deep learning, machine learning, and NLP) and their applications in digital marketing and shaping customer experience. At the same time, the marginal number of citations of older sources (pre-2000) confirms that this field is modern in nature and strongly related to technological development, and traditional management or marketing concepts are rarely invoked here.

The conclusions from RPYS emphasise that AI in marketing is a relatively young but rapidly growing research area, in which fresh and interdisciplinary sources of knowledge are crucial. It is also a hint for future researchers to pay special attention to the literature developed in the last 5-10 years as a foundation for further theoretical and empirical analyses.

Building on the citation-structure analysis presented above, the authors consider the following qualitative inferences to be salient: (i) a structural recency dependence in AI-MarTech, whereby rapid methodological turnover and tool diffusion after 2015 render older contributions progressively less central; (ii) a short method -> application lag, with the 2016-2019 spikes consistent with breakthroughs in core AI (e.g., deep learning and NLP) being followed by accelerated uptake in digital marketing and customer-experience contexts, a proposition that is testable via time-sliced RPYS and cross-correlations between method-centric and application-centric citation series; and (iii) the low salience of pre-2000 sources, which suggests limited path-dependence on legacy marketing theory and lagging diffusion of governance and human-centred concerns (trust, usability, perceived risk, and ethics), motivating longitudinal tracking (e.g., rolling five-year windows) to observe when these themes integrate into outcome-oriented research.

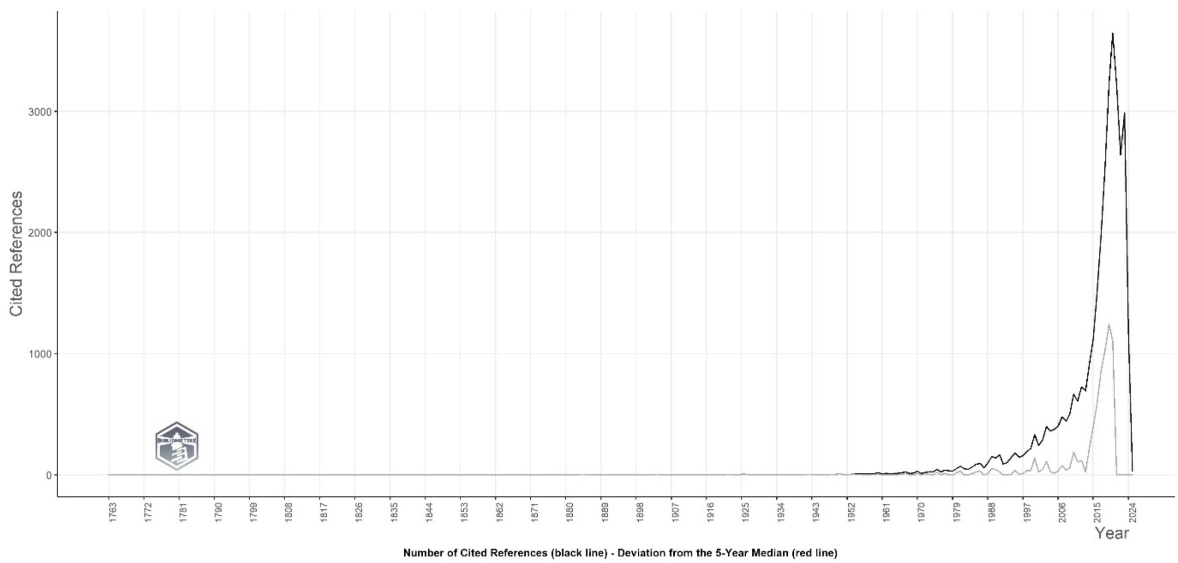

Fig. 5. Analysis of cited sources by year of publication

Source: author's elaboration on the basis of R software.

3.8. Authors' keyword analysis in AI and marketing technology publications

The analysis of the frequency of keywords used by the authors clearly indicates that "artificial intelligence" (233 occurrences) is definitely the dominant research topic in the analysed literature. The high frequency of this concept - in different spelling variants (including "AI" - 29 times, "artificial intelligence (AI)" - 21 times, "machine learning" - 30 times, "generative AI" - 11 times) - indicates the central place of artificial intelligence in research on the border between marketing and new technologies.

The general term "marketing" (56) came second, followed by the more specialised term "digital marketing" (33), confirming that the area of digital marketing is the main context for AI applications. A significant number of occurrences also concern related technologies and concepts, such as "big data" (19), "internet of things" (14), "ChatGPT" (15), "chatbots" and "chatbot" (17 in total), "deep learning" (8) or "augmented reality" (7), which proves the interdisciplinary nature of the analysed area.

Emerging keywords such as "technology adoption" (12), "digital transformation" (10), and "customer experience" (10) suggest that research focuses not only on the technology itself, but also on the process of its implementation and its impact on consumer experience. Additionally, the presence of the terms "social media" (12), "advertising" (7) and "e-commerce" (7) indicates strong links between AI and the areas of application in digital communication and sales.

Taken together, the results of this analysis confirm that AI in marketing is a complex, dynamic topic, deeply embedded in the realities of contemporary digital transformation, encompassing technological, consumer, communication and strategic issues.

The authors' reading of the keyword distribution may suggest a three-layer structure of the AI-MarTech discourse. First, an infrastructural, computational layer appears to coalesce around the family of terms related to artificial intelligence (artificial intelligence, AI, artificial intelligence (AI), machine learning, generative AI, and ChatGPT), complemented by big data, the internet of things, deep learning, and augmented reality. This concentration may be taken to indicate an AI-centric identity for the field, in which the technical backbone provides methods and data substrates for marketing applications. Second, an application layer (including marketing, digital marketing, social media, advertising, e- commerce, retailing, and customer/client experience) appears to suggest that AI is predominantly framed in service of market outcomes and customer-facing processes rather than as an end in itself. Third, an organisational-implementation layer (technology, innovation, technology adoption, adoption, and digital transformation) may indicate growing attention to how AI is embedded within firms and workflows, not only what it does.

Tab. 13. Keywords analysis of article authors

Lp.	Authors' keywords	Occurrence
1	Artificial intelligence	233
2	Marketing	56
3	Digital marketing	33
4	Machine learning	30
5	AI	29
6	Technology	26
7	Artificial intelligence (ai)	21
8	Big data	19
9	Chatgpt	15
10	Internet of things	14
11	Innovation	12
12	Social media	12
13	Technology adoption	12
14	Tourism	12
15	Generative AI	11
16	Generative artificial intelligence	11
17	Covid-19	10
18	Client experience	10
19	Digital transformation	10
20	Adoption	9
21	Chatbots	9
22	Chatbot	8
23	Deep learning	8
24	Information technology	8
25	Retailing	8
26	Social media marketing	8
27	Advertising	7
28	Augmented reality	7
29	Digital technologies	7
30	ecommerce	7

Source: study by the author in R software, Scopus database.

Within this configuration, the simultaneous presence of ChatGPT/generative AI and chatbot(s) may point to evolution rather than rupture: conversational interfaces likely persist, while underlying models shift towards large-scale paradigms. The occurrence of tourism and COVID-19 may reflect sectoral and temporal sub-streams; their moderate frequencies could suggest context-specific lines of inquiry rather than field-defining pillars. From a maturity perspective, the relatively high frequencies of umbrella labels (e.g., artificial intelligence and marketing) compared with more granular constructs (e.g., advertising and customer experience) are consistent with the view that the domain is consolidating around higher-order categories while differentiating mechanisms and outcomes in parallel. Notably, the limited visibility of governance/ethics vocabulary (e.g., trust, transparency, and fairness) among the most frequent terms may signal - at least in this sample - an underrepresentation of normative and risk-management concerns at the top of the frequency distribution.

In light of these observations, the authors suggest as a promising direction for future research the systematic linking of the implementation layer (adoption and digital transformation) with outcome constructs (e-commerce, advertising, and customer experience), coupled with the early integration of quality and safety dimensions (e.g., transparency and reliability). Such a shift would allow the literature to move beyond frequency counts towards explanatory models of impact.

4. Discussion of the results

Based on the bibliometric analysis, it can be concluded that the state of research on artificial intelligence in the context of marketing technologies (research question PB1) is at a stage of dynamic development, especially after 2020. The literature covers a wide spectrum of AI applications - from process automation, through personalisation of marketing activities, to the development of generative AI and recognition of customer emotions. The evolution of the literature (research question PB2) shows a clear shift in researchers' interests from the tool level (e.g., machine learning and big data) to topics related to customer experience, AI ethics and emotion-based communication. Particularly intensive development of the literature took place in 2019-2023, which is reflected both in the number of publications and average citations per article.

Among the leading research centres (research question PB3), Queensland University of Technology, Swansea University, The Hong Kong Polytechnic University and UCSI University stand out, which not only generate a large number of publications but also actively participate in international research projects. The largest number of publications comes from the United States, India, and China, while the highest average citation impact is recorded by research conducted in the United Kingdom, France, and Australia.

The analysis also allows for the identification of existing gaps and limitations of the literature (research question PB4), among which the fragmentation of theoretical approaches, the insufficient number of empirical studies in the context of AI applications in various industries and the insufficient consideration of ethical and social aspects come to the fore. Possibilities for further research include human-centred AI development, AI integration with customer experience management (Customer Experience, in short CX), creating real-time predictive models and exploring emotional aspects of marketing communication. The identified areas constitute important directions for future research exploration and market practices.

The bibliometric evidence positions AI-MarTech as a rapidly advancing yet already structured domain. A stable backbone, an AI-marketing core flanked by technology adoption and market applications/digital commerce, organises the literature, while human-centred factors and generative AI/ChatGPT remain early-stage but increasingly consequential. RPYS confirms strong recency, consistent with fast methodological turnover. Beyond mapping, this study contributes a unifying field architecture (innovation -> adoption -> outcomes), a measurement-sensitive triangulation (constant coupling/thresholds with LCS vs GCS and Index vs Authors' keywords), and keyword-level diagnostics that identify commerce as the most central transversal integrator and AI as an infrastructural "basic" theme, with high-density yet peripheral niches (sustainability and economic/social effects) poised for integration. Going forward, further research should (i) model causal chains from adoption to decision-making to outcomes using A/B and quasi-experiments and standardised metrics (ROI, incrementality, CLV, and retention), (ii) bridge high-density niches to outcome streams, and (iii) develop governance for generative AI (guardrails, disclosure and XAI) explicitly tied to measurable impact. These conclusions provide a decision-relevant baseline for cumulative theory building and empirical work in AI-MarTech.

Conclusions

This article maps the AI-MarTech literature using a transparent, replicable bibliometric pipeline over 492 peer-reviewed publications (1987-2025). The field exhibits a stable backbone with an AI-marketing core (the largest and most central), flanked by technology adoption and market applications/digital commerce. Two smaller clusters: human-centred factors and generative AI/ChatGPT are early-stage in network terms but increasingly consequential, reflecting a shift towards governance, trust, and safety alongside performance. Beyond description, the study contributes (i) an integrative field architecture, innovation -> adoption -> outcomes, linking fragmented streams; (ii) measurement-sensitive triangulation (constant coupling/thresholds, varied impact metric: LCS vs GCS; varied label source: Index vs Authors' keywords) that shows how specification choices alter perceived salience (e.g., perception vs virtual influencers); and (iii) keyword-level diagnostics identifying commerce as the most central transversal integrator and AI as an infrastructural "basic" theme, with high-density yet peripheral niches (sustainability; economic/social effects) poised for integration. These results provide a robust baseline for cumulative theory building and decision-relevant empirical work.

Scientific contribution and research agenda

The authors' findings AI-MarTech as a substantive and fast-consolidating domain with a coherent field architecture. Empirically, the study articulates and supports a three-stage spine: innovation -adoption -market outcomes, augmented by human-centred moderators (trust, usability, perceived risk, and ethics) and a generative-AI accelerator that increasingly conditions speed and governance of diffusion. This integrative framing reconciles previously fragmented streams by positioning the AI-marketing core as the system's hub and by specifying how adjacent lines of inquiry (adoption processes and market applications) connect to outcome metrics. In parallel, keyword-level diagnostics clarify functional roles within the network: commerce operates as a transversal integrator (highest centrality), artificial intelligence functions as an infrastructural "basic" theme, while sustainability and economic/social effects appear as high-density yet peripheral niches that are poised for integration with outcome-oriented research. The temporal profile (post-2015 surge) and the geography of contributions further contextualise the evidence base, distinguishing volume leaders from high-impact ecosystems and, thus, informing collaboration strategies and external validity.

A second scientific contribution is measurement-sensitive triangulation. Holding the coupling method and thresholds constant while varying the impact metric (LCS vs GCS) and the label source (Index vs Authors' keywords) demonstrates how specification choices shift perceived salience. Under GCS + Authors' keywords, adoption and digital/commerce gain visibility and emergent topics are labelled with greater precision (e.g., virtual influencers), whereas LCS + Index Keywords emphasises influence within the analysed corpus and aggregates emergent under broader notions (e.g., perception). This dual-specification design provides a template for robustness checks in bibliometric mapping and encourages transparent reporting practices in future studies.

Taken together, these results yield a focused research agenda. First, move from adoption to outcomes by modelling causal chains, adoption -> decision-making -> commerce, using A/B and quasi-experimental designs, panel data, and robustness checks that link interventions to ROI, incrementality, CLV, retention, and related performance indicators. Second, bridge high-density niches to the core by operationalising sustainable development and economic/social effects with comparable outcome metrics (e.g., eco-ROI and robustness/fairness scores), thereby elevating their network centrality through explicit links to commerce and customer experience. Third, advance the governance of generative AI by developing guardrails, hallucination audits, disclosure practices, and XAI protocols, and by tying quality and safety directly to measurable market outcomes; track when generative AI transitions from an emergent theme to a motor theme. Fourth, scale human-centred moderators through cross-cultural, longitudinal designs on trust, usability, emotion, perceived risk, and ethics; use both Index- and author-labelled lenses to capture broad and fine-grained human factors. Fifth, pursue methodological pluralism with transparency by reporting dual impact metrics (LCS and GCS) and dual labelling sources (Index and Authors' keywords) to separate stable signals from specification-sensitive patterns; where feasible, preregister bibliometric protocols. Finally, conduct sector-specific transfer tests for emergent/peripheral topics (e.g., virtual influencers, speech recognition), connecting sectoral insights to mainstream metrics (conversion, average order value, churn) to move these themes towards the field's core.

The scholarly payoff of this programme is threefold: it sharpens construct clarity around AI-MarTech, standardises evaluation across studies, and tightens the linkage between human-centred governance and economic value. In doing so, it provides a robust baseline for cumulative theory building and decision-relevant evidence that can guide both academic inquiry and managerial practice.

Limitations

As with all bibliometric studies, this research is subject to several limitations that should be acknowledged when interpreting the findings.

First, the analysis was limited to two major academic databases, Scopus and Web of Science, which, despite their breadth and credibility, do not capture the entirety of relevant literature. Important insights published in monographs, book chapters, or regional journals not indexed in these databases may have been omitted. Additionally, only English-language publications were considered, potentially excluding valuable contributions from non-English-speaking academic communities.

Second, the bibliometric indicators used, such as citation counts, centrality, and density, measure structural influence, but not necessarily conceptual depth or practical impact. Highly cited papers may reflect early interest rather than long-term theoretical contribution, while emerging themes might be undervalued due to their novelty.

Third, the keyword-based search strategy, although rigorously developed, may have excluded works that address AI and MarTech indirectly or under alternative terminologies. This could have affected the inclusivity of thematic clusters.

Despite these limitations, the study provides a strong empirical foundation for future research. Subsequent investigations should complement bibliometric approaches with qualitative content analysis, systematic reviews, or meta-analyses to explore conceptual relationships in greater depth. Future research may also address the ethical, emotional, and regulatory implications of AI in marketing, especially in light of developments in generative AI, human-AI interaction, and data privacy.

Such directions will contribute to a more integrated understanding of the technological, organisational, and societal dynamics shaping the evolution of AI-powered marketing ecosystems.

Practical implications

The findings carry several decision-relevant implications for marketing professionals, technology developers, and policy makers operating at the AI-MarTech interface. First, the identification of five thematic clusters, anchored in an AI-marketing core and flanked by technology adoption and digital-commerce, with human-centred factors and generative AI/ChatGPT as early-stage streams, offers a prioritisation map for capability building and investment. Mature areas should be targeted for near-term deployment, while emergent streams merit measured experimentation and structured monitoring.

Second, the rise of generative AI together with human-centred approaches underscores that performance gains must be coupled with governance and experience quality. Practitioners should integrate technical capacities (e.g., machine learning and NLP) with explainability, disclosure, and transparency mechanisms, and evaluate interventions using standardised outcome metrics (e.g., ROI, incrementality, CLV, and retention) and field experiments (A/B and quasi-experimental designs).

Third, the international distribution of impactful research, particularly contributions from the UK, France, Australia, and dynamic Asian ecosystems, suggests that cross-border partnerships with universities and R&D centres can accelerate transfer from method to application. Firms may benefit from co-developing evaluation protocols (e.g., shared benchmarks, reproducible pipelines) that reflect both global citation resonance and domain-specific constraints.

Finally, the observed underrepresentation of ethical and societal considerations implies that effective MarTech deployment should extend beyond technological efficiency to long-term stakeholder trust, data governance, and regulatory compliance. Establishing guardrails for generative AI (e.g., hallucination audits, risk registers, and XAI practices) and linking them explicitly to market outcomes can align innovation speed with safety and accountability.

Literature

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959-975. doi: 10.1016/j.joi.2017.08.007

Bornmann, L., & Daniel, H. (2008). What do citation counts measure? A review of studies on citing behavior. *Journal of Documentation*, *64*(1), 45-80. doi: 10.1108/00220410810844150

Chotisarn, N., & Phuthong, T. (2025). Mapping the landscape of marketing technology: Trends, theories and trajectories in ecosystem research. *COGENT BUSINESS & MANAGEMENT*, *12*(1). doi: 10.1080/23311975.2024.2448608

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24-42. doi: 10.1007/s11747-019-00696-0

de Andrés-Sánchez, J., & Gené-Albesa, J. (2023). Explaining Policyholders' Chatbot Acceptance with an Unified Technology Acceptance and Use of Technology-Based Model. J*ournal of Theoretical and Applied Electronic Commerce Research*, *18*(3), 1217-1237. Scopus. doi: 10.3390/jtaer18030062

De Luca, L. M., Herhausen, D., Troilo, G., & Rossi, A. (2021). How and when do big data investments pay off? The role of marketing affordances and service innovation. *Journal of the Academy of Marketing Science*, *49*(4), 790-810. doi: 10.1007/s11747-020-00739-x

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285-296. doi: 10.1016/j.jbusres.2021.04.070

Glänzel, W., & Schubert, A. (2004). Analysing scientific networks through co-authorship. In W. H. F. Moed, W. Glänzel, & U. Schmoch (Eds.), *Handbook of Quantitative Science and Technology Research* (pp. 257-276). Berlin, Germany: Springer.

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*(1), 30-50. doi: 10.1007/s11747-020-00749-9

Huang, M.-H., & Rust, R. T. (2024). The Caring Machine: Feeling AI for Customer Care. *Journal of Marketing*, *88*(5), 1-23. doi: 10.1177/00222429231224748

Kietzmann, J., Paschen, J., & Treen, E. (2018). Artificial Intelligence in Advertising: How Marketers Can Leverage Artificial Intelligence Along the Consumer Journey. *Journal of Advertising Research*, *58*(3), 263-267. doi: 10.2501/JAR-2018-035

Klincewicz, K. (2009). The use of bibliometrics in management science. *Problemy Zarządzania*, *7*(4), 130-156.

Klincewicz, K., Żemigała, M., & Mijal, M. (2012). *Bibliometria w zarządzaniu technologiami i badaniami naukowymi* [*Bibliometrics in technology and research management*]. Warszawa, Poland: Ministerstwo Nauki i Szkolnictwa Wyższego.

Kumar, V., Ashraf, A. R., & Nadeem, W. (2024). AI-powered marketing: What, where, and how? *International Journal of Information Management*, *77*, 102783. doi: 10.1016/j.ijinfomgt.2024.102783

Kumar, V., & Kotler, P. (2024). *TRANSFORMATIVE MARKETING: Combining new age technologies and human insights*. Cham, Switzerland: Palgrave Macmillan.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. *Journal of Marketing*, *80*(6), 69-96. doi: 10.1509/jm.15.0420

Leydesdorff, L. (2001). *The Challenge of Scientometrics: The Development, Measurement, and Self-Organization of Scientific Communications*. California, USA: Universal Publishers.

Massimo, A., & Cuccurullo, C. (2017). Bibliometrix: An R-Tool for Comprehensive Science Mapping Analysis. *Journal of Informetrics*, *11*(4), 959-975.

Moed, H. F., Glänzel, W., & Schmoch, U. (2004). *Handbook of quantitative science and technology research: The use of publication and patent statistics in studies of S & T systems*. Dordrecht, Netherlands: Kluwer Academic Publishers.

Rust, R. T. (2020). The future of marketing. *International Journal of Research in Marketing*, *37*(1), 15-26. doi: 10.1016/j.ijresmar.2019.08.002

Small, H. (1999). Visualizing science by citation mapping. *Journal of the American Society for Information Science*, *50*(9), 799-813. doi: 10.1002/(SICI)1097-4571(1999)50:9<799::AID-ASI9>3.0.CO;2-7

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. J*ournal of Business Research*, *104*, 333-339. doi: 10.1016/j.jbusres.2019.07.039

Teece, D. J. (2008). Dosi's technological paradigms and trajectories: Insights for economics and management. *Industrial and Corporate Change*, *17*(3), 507-512. doi: 10.1093/icc/dtn014

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509-533. doi: 10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

Thakur, J., & Kushwaha, B. P. (2024). Artificial intelligence in marketing research and future research directions: Science mapping and research clustering using bibliometric analysis. *Global Business and Organizational Excellence*, *43*(3), 139-155. doi: 10.1002/joe.22233

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a New Dominant Logic for Marketing. *Journal of Marketing*, *68*(1), 1-17. doi: 10.1509/jmkg.68.1.1.24036

Wirth, N. (2018). Hello marketing, what can artificial intelligence help you with? *International Journal of Market Research*, *60*(5), 435-438. doi: 10.1177/1470785318776841

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, *29*(5), 907-931. doi: 10.1108/JOSM-04-2018-0119

Żemigała, M. (2018). Analiza bibliometryczna badań nad innowacjami w sektorach niskich technologii. *Zeszyty Naukowe. Organizacja i Zarządzanie / Politechnika Śląska*, *118*, 703-711. doi: 10.29119/1641-3466.2018.118.55