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Mapping a Decade of AI-Generated Content in Digital Marketing: A Bibliometric Analysis (2016-2025)

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ABSTRACT

Artificial-intelligence-generated content (AIGC), the autonomous production of text, images, audio and video by generative models, has rapidly become a central concern for digital-marketing scholarship and practice. This study maps the intellectual structure and evolution of research at the AIGC-digital-marketing intersection. Following PRISMA guidelines, 1400 Scopus-indexed articles and reviews published between 2016 and 2025 were retrieved and analysed in Bibliometrix and VOSviewer, combining performance analysis with science mapping. Annual output grew at a compound rate of 54.15% per year across three phases: A nascent period (2016-2019), gradual exploration (2020-2022) and explosive growth after late 2022, with 2025 alone contributing 52.6% of the corpus. Production is anchored by a United States-China dual core, with India acting as a bridging node. Co-citation and keyword analyses reveal a knowledge base that fuses established technology-adoption theories and structural-equation methodology with recent generative-AI manifestos, organised around four themes: Content production, distribution channels, audience reach and responsible governance. Tool-level analysis shows that the literature is overwhelmingly text-centric (ChatGPT and the GPT family), while image and video generators and Asian social platforms remain under-examined. The study offers, to the best of our knowledge, one of the first decade-scale maps of this field, together with a structured agenda for future research.

Keywords: AI-Generated Content, Generative Artificial Intelligence, Digital Marketing, Bibliometric Analysis, Science Mapping
JEL Classifications: M31, M37, O33

1. INTRODUCTION

The public release of ChatGPT in late 2022 marked a turning point for the commercial application of artificial intelligence (Huh et al., 2023; Peres et al., 2023; Wahid et al., 2023). Within months, generative systems capable of producing fluent text, photorealistic images, synthetic voices and video moved from research laboratories into the daily workflows of marketers, advertisers and content creators (Peres et al., 2023; Wahid et al., 2023). Artificial-intelligence-generated content, or AIGC, is the umbrella term for the output of these systems (Wahid et al., 2023). It now denotes a class of technologies that can draft advertising copy, design visual assets, personalise messages at scale, power conversational commerce and synthesise customer insight in near real time (Davenport et al., 2020; Gupta et al., 2024; Huang and Rust, 2021; Kietzmann et al., 2018). For a discipline whose raw material is content and whose currency is attention, the implications are profound (Peres et al., 2023; Wahid et al., 2023).

Digital marketing is, in many respects, the natural proving ground for these capabilities (Davenport et al., 2020; Huang and Rust, 2021). The field already operates through data-rich, automated and platform-mediated channels in which content is produced, distributed, targeted and measured continuously (Ford et al., 2023; Kietzmann et al., 2018). Generative models slot directly into this machinery: they reduce the marginal cost of content production, enable hyper-personalisation, and open new creative and analytical possibilities across the consumer journey (Gupta et al., 2024; Peres et al., 2023;

Wahid et al., 2023). At the same time, they raise acute concerns about authenticity, transparency, intellectual property, misinformation and consumer trust, concerns crystallised by the emergence of deepfakes and AI-generated advertising (Campbell et al., 2022; Huh et al., 2023; Mijan et al., 2023). The resulting tension between efficiency and responsibility defines much of the contemporary research conversation (Campbell et al., 2022; Ford et al., 2023).

Scholarly attention has expanded at a pace that few research fronts have matched (Huh et al., 2023; Peres et al., 2023). What began as a scattering of technically oriented studies on generative adversarial networks (GANs), recommender systems and natural-language processing has, since 2023, become a torrent of work spanning advertising, retailing, consumer behaviour, service management, tourism and marketing education (Adomavicius and Tuzhilin, 2005; Devlin et al., 2019; Goodfellow et al., 2014; Guha et al., 2024; Gursoy et al., 2023; Vaswani et al., 2017). This rapid, fragmented growth creates a familiar problem. It becomes difficult to discern the underlying structure of the field: who is contributing, which ideas anchor the conversation, how themes relate, and where the white spaces lie. Bibliometric analysis is well suited to this problem, because it uses the quantitative footprints of publication and citation to reconstruct the intellectual and social architecture of a domain (Aria and Cuccurullo, 2017; Donthu et al., 2021; van Eck and Waltman, 2010; Zupic and Čater, 2015).

Several reviews have begun to chart adjacent territory. Recent bibliometric and systematic studies have examined generative AI in marketing more broadly (Prasanna and Kushwaha, 2025), virtual influencers (Pushparaj et al., 2025) and the effects of generative AI on consumer behaviour (Panda et al., 2026). These typically draw on corpora of a few hundred documents and concentrate on the post-2022 surge. They are valuable, but they leave three gaps. First, most are bounded to the generative-AI moment and omit the pre-ChatGPT foundations (2016-2021) on which the field was built. Second, few descend to the level of specific AIGC tools, so the actual distribution of scholarly attention across text, image and video generators remains undocumented. Third, the geographic and platform dimensions (the role of Asian markets and Asian social platforms) are rarely examined, even though publication output is increasingly concentrated outside the traditional Western core (Liu and Binti Mijan, 2024).

This study addresses these gaps by mapping a full decade of research at the AIGC-digital-marketing intersection. Using a PRISMA-screened corpus of 1400 Scopus-indexed documents (2016-2025), substantially larger and longer than comparable reviews, it pursues four research questions. RQ1: How has scholarly output evolved over the decade, and what growth dynamics characterise the field? RQ2: Which authors, sources and documents constitute its productive and intellectual core? RQ3: What is the conceptual structure of the field, and how have its themes shifted over time? RQ4: How is scholarly attention distributed across AIGC tools, geographies and platforms, and where do the principal research gaps lie?

The contribution is threefold. Empirically, the study provides, to the best of our knowledge, one of the first decade-scale, tool-aware maps of the field, integrating performance analysis with science mapping across authors, sources, references, keywords, countries and tools. Conceptually, it organises a fragmented literature into four coherent themes (content production, distribution channels, audience reach and responsible governance) and traces the late-period centralisation of ethics-related concerns. Practically, it surfaces concrete white spaces, notably the text-centric bias of current scholarship and the limited treatment of Asian platforms and translates these into an agenda for research and management. The remainder of the paper is organised as follows. Section 2 reviews the conceptual and historical background; Section 3 details the data and methods; Section 4 reports the bibliometric results; Section 5 is the discussion; and Section 6 concludes the paper with implications.

2. LITERATURE REVIEW

2.1. Conceptualising AIGC in Digital Marketing

AIGC refers to media artefacts (text, images, audio, video and code) produced wholly or partly by generative artificial-intelligence systems rather than by human authors (Feuerriegel et al., 2024; Goodfellow et al., 2014; OpenAI, 2023). The category spans large language models (LLMs) such as the GPT family, diffusion-based image generators such as stable diffusion and DALL-E, and emerging video and voice synthesisers (Brown et al., 2020; Ho et al., 2020; Rombach et al., 2022; Vaswani et al., 2017). Although popular usage now favours "generative AI," the term AIGC usefully foregrounds the content itself (the output that marketers commission, edit, distribute and are accountable for) rather than the underlying model (Feuerriegel et al., 2024; Wahid et al., 2023). This output orientation matters analytically in marketing, where the unit of value is the message delivered to a consumer, not the architecture that produced it (Mijan and Abdullah, 2019).

Within digital marketing, AIGC intersects with several established streams. In content and creative strategy, generative models reframe long-standing questions about message design, brand voice and creative labour (Kietzmann et al., 2018; Wahid et al., 2023). In personalisation and targeting, they extend the logic of data-driven marketing by generating individualised content rather than merely selecting among pre-existing variants (Davenport et al., 2020; Huang and Rust, 2021; Puntoni et al., 2021). In channel and platform management, conversational agents and recommender systems mediate the consumer's encounter with brands (Adomavicius and Tuzhilin, 2005; Kietzmann et al., 2018). In marketing ethics and governance, synthetic media revive concerns about deception, manipulation and trust in acute new forms (Campbell et al., 2022; Chesney and Citron, 2019; Mirsky and Lee, 2021). AIGC is therefore best understood not as a single topic but as a general-purpose capability that diffuses across the marketing function, which is precisely why a structural, field-level mapping is warranted (Davenport et al., 2020; Huang and Rust, 2021).

2.2. Pre-ChatGPT Foundations (2016-2021)

Although public discourse dates the field to 2022, its scholarly foundations were laid earlier and are essential to understanding its present shape (Huh et al., 2023; Peres et al., 2023). Between 2016 and 2021 the relevant literature was predominantly technical and concentrated in computing and information-systems outlets (Adomavicius and Tuzhilin, 2005; Devlin et al., 2019; Goodfellow et al., 2014; Vaswani et al., 2017). Three sub-streams stand out. The first centred on generative adversarial networks and their commercial applications; representative work used GANs to improve classification in credit-card fraud detection (Fiore et al., 2019; Goodfellow et al., 2014), establishing generative modelling as a tool for data augmentation and risk management in transactional settings. The second concerned predictive analytics for customer management, exemplified by hybrid algorithms for customer-churn prediction that combined logistic regression with decision trees (Adomavicius and Tuzhilin, 2005; De Caigny et al., 2018). The third addressed synthetic media and its risks, most influentially through overviews of media forensics and deepfakes (Chesney and Citron, 2019; Mirsky and Lee, 2021; Verdoliva, 2020), which framed authenticity and detection as first-order problems well before generative text entered the mainstream.

These foundations matter for three reasons. They explain the strong and persistent presence of machine-learning and deep-learning vocabulary in the field's keyword structure; they account for the prominence of technical venues among its most productive sources; and they reveal that the responsible-governance agenda later associated with generative text in fact originated in the earlier deepfake and information-integrity literature (Campbell et al., 2022; Chesney and Citron, 2019; Mirsky and Lee, 2021). A decade-scale lens is thus necessary to recover the continuity between the field's technical prehistory and its current managerial orientation, a continuity that post-2022 reviews necessarily miss.

2.3. The Generative Turn and the Case for Bibliometric Synthesis

The arrival of accessible LLMs reoriented the field almost overnight (Brown et al., 2020; Noy and Zhang, 2023; OpenAI, 2023). Agenda-setting commentaries argued that generative conversational AI would reshape research, teaching and practice across disciplines (Dwivedi et al., 2023; Huh et al., 2023; Ooi et al., 2025; Paul et al., 2023) and, within marketing specifically, would affect the entire knowledge-production and managerial value chain (Peres et al., 2023; Wahid et al., 2023). In parallel, work on the consumer-facing risks of synthetic media matured into frameworks for understanding responses to deepfakes and AI-generated advertising (Campbell et al., 2022; Huh et al., 2023), and theoretical syntheses began to specify the antecedents and impacts of generative-AI adoption (Gupta et al., 2024; Paul et al., 2023). The result is a literature that is at once conceptual and applied, optimistic and cautionary, and distributed across many disciplinary homes.

This combination of explosive growth, disciplinary breadth and conceptual fragmentation is what makes a bibliometric synthesis both timely and methodologically appropriate. Narrative reviews struggle to remain comprehensive when a field doubles in size within a single year; bibliometric methods, by contrast, scale gracefully and offer reproducible, quantitative evidence of structure and trajectory (Aria and Cuccurullo, 2017; Donthu et al., 2021; van Eck and Waltman, 2010). Existing reviews have demonstrated the value of this approach for the generative-AI moment, but none yet provides a decade-scale, tool-level and geographically attentive account (Ford et al., 2023; Paul et al., 2023). The present study is designed to fill that role.

3. METHODOLOGY

3.1. Research Design

The study adopts a bibliometric design that combines performance analysis with science mapping (Cobo et al., 2011; Donthu et al., 2021; Moed, 2005). Performance analysis quantifies the productivity and impact of research constituents (publications, authors, sources, countries and documents), while science mapping reconstructs the relationships among them through co-authorship, co-citation, bibliographic coupling and keyword co-occurrence (Callon et al., 1983; Kessler, 1963; Newman, 2001; Small, 1973; Zupic and Čater, 2015). This dual approach suits a young, fast-growing and interdisciplinary field, because it offers a reproducible, quantitative account of structure and trajectory that complements, rather than replaces, qualitative reading (Boyack and Klavans, 2010; Cobo et al., 2011). All analyses were conducted in the Bibliometrix R package (Aria and Cuccurullo, 2017) and the VOSviewer mapping environment (van Eck and Waltman, 2010), the two most widely used and validated tools in the field (Cobo et al., 2011; van Eck and Waltman, 2010; Waltman et al., 2010).

3.2. Data Source and Search Strategy

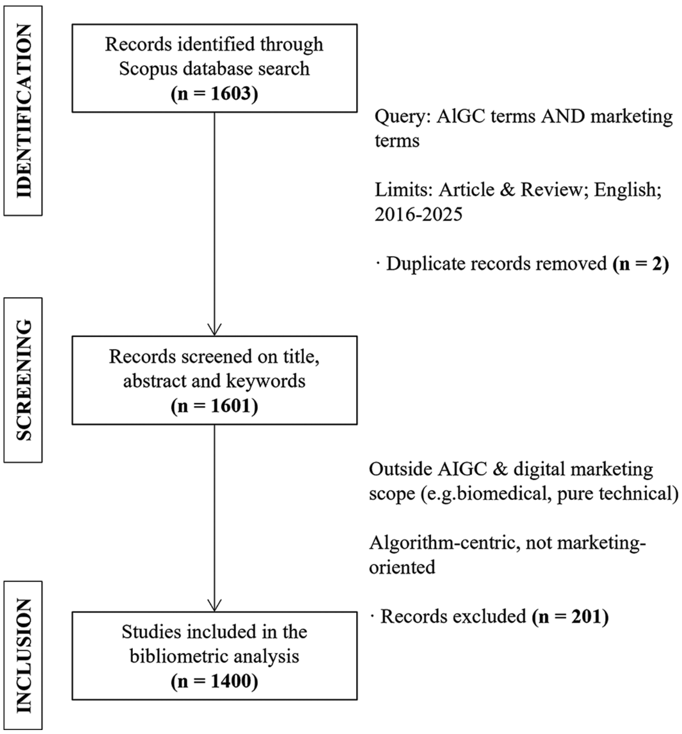
Scopus was selected as the single data source (Falagas et al., 2008; Mongeon and Paul-Hus, 2016; Singh et al., 2021). As the largest curated abstract-and-citation database of peer-reviewed literature, it offers broad disciplinary coverage and consistent, structured metadata for authors, affiliations, references and keywords, all essential for reliable science mapping (Falagas et al., 2008; Mongeon and Paul-Hus, 2016; Pranckutė, 2021). The decision to rely on a single database, rather than merging Scopus with Web of Science, was deliberate. Single-source designs avoid the record-matching errors, duplicate-resolution artefacts and metadata inconsistencies that frequently arise when databases with different indexing conventions are combined, at the acceptable cost of omitting a minority of venues indexed elsewhere (Gusenbauer and Haddaway, 2020; Mongeon and Paul-Hus, 2016; Singh et al., 2021).

The search was executed on 6 June 2026 and combined two concept blocks with the Boolean AND operator (Booth et al., 2016; Gusenbauer and Haddaway, 2020). The AIGC block covered terms for generative AI and AI-generated content; LLMs, the GPT family and ChatGPT; conversational assistants including Gemini and Copilot; diffusion models and named image and video generators such as stable diffusion, DALL-E, Midjourney and Sora; text-to-image and text-to-video synthesis; foundation and multimodal generative models; generative adversarial networks; and deepfakes and synthetic media. The digital-marketing block covered terms for marketing, advertising and branding; consumer behaviour and consumer or customer engagement; e-commerce and social commerce; influencers; purchase intention; word-of-mouth; endorsements; and marketing communication. The complete query string is reported in Appendix A. Results were limited to journal articles and reviews published between 2016 and 2025 and written in English.

3.3. Screening and Corpus Construction

Screening followed the PRISMA framework (Page et al., 2021) and is summarised in Figure 1. The initial query identified 1,603 records. After removing 2 duplicates, 1601 records were screened on title, abstract and keywords. A total of 201 records were excluded as lying outside the AIGC × digital-marketing scope, chiefly purely technical and algorithm-centric studies with no marketing orientation, together with biomedical and other clearly unrelated work. A very small number of exceptionally highly cited cross-disciplinary AI papers (most visibly one drug-discovery review) were retained where they were strongly embedded in the citation structure of the corpus and are explicitly flagged in Section 4.3 rather than silently removed. The broad inclusion of brand-related terms also produced a small number of "brand new" false positives, which were identified and removed during manual screening. The procedure yielded a final corpus of 1400 documents. Two characteristics of the corpus warrant comment. First, it comprises 1332 articles and 68 reviews drawn from 748 sources, with 73625 cited references in total, a mean of 20.03 citations per document and a mean document age of 2.26 years; the low average age reflects the field's recent acceleration. Second, the sparse output of the earliest years (2016-2019) is not a data artefact but an accurate reflection of the field's youth. These years constitute a genuine take-off pre-history, and their structural indicators should be read as indicative rather than definitive.

Figure 1: PRISMA flow diagram of the identification, screening and inclusion process



3.4. Analytical Procedures and Indicators

Performance indicators were computed in Bibliometrix and include annual scientific production, the compound annual growth rate (AGR), total publications (TP) per author, source and country, total citations (TC), citations per year (TC/Year) and the h-index. Author productivity was assessed against Lotka's law (Lotka, 1926). Science maps were produced in VOSviewer using association-strength normalisation and full counting throughout. The principal mapping analyses, with their inclusion thresholds, were author co-authorship (minimum 3 documents per author; Figure 2); source co-citation (minimum 20 citations per source; Figure 3); reference co-citation (minimum 15 citations per cited reference; Figure 4); and author-keyword co-occurrence (minimum 8 occurrences per keyword; Figure 5). The keyword analysis was

Figure 2: Author co-authorship network (VOSviewer)

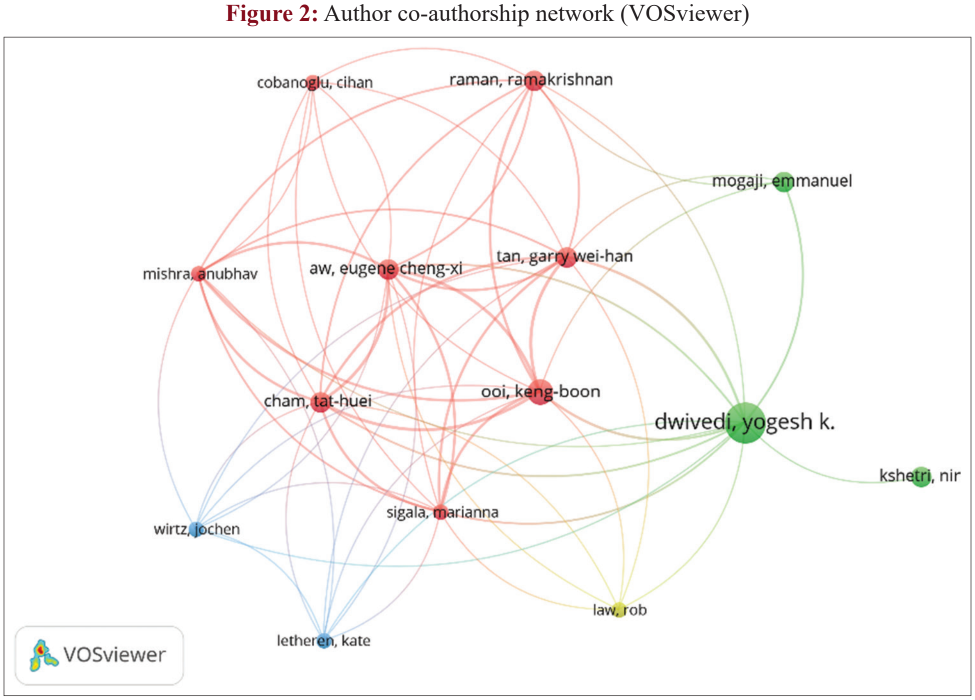


Figure 3: Source co-citation network

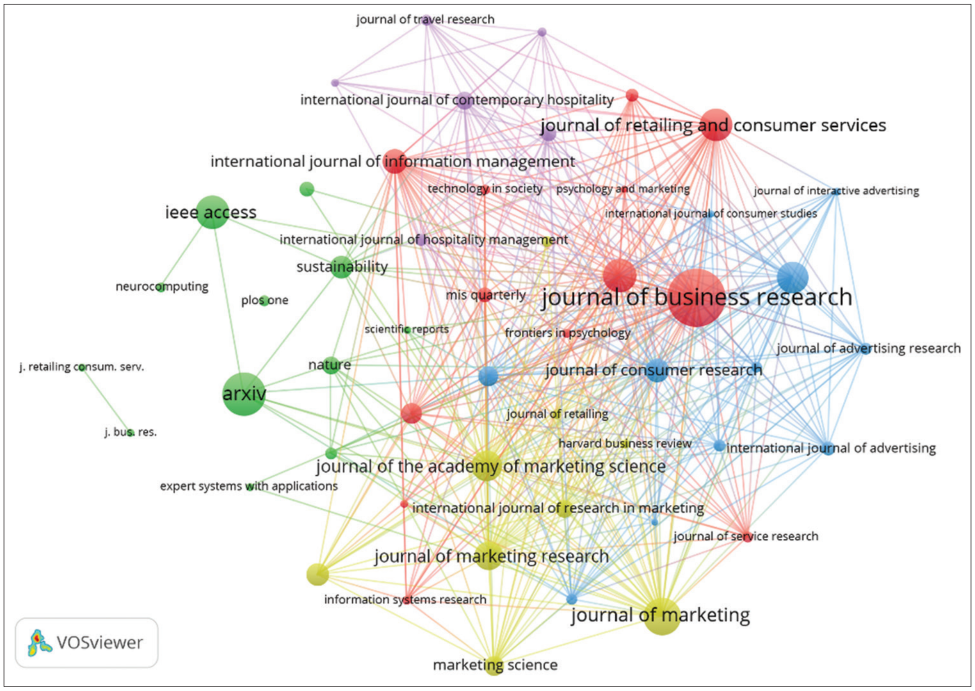
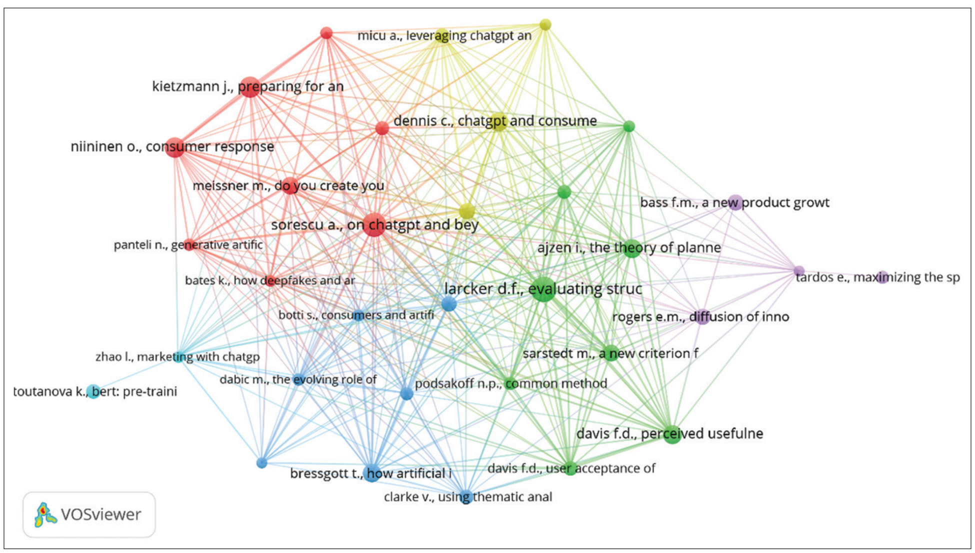


Figure 4: Reference co-citation network



complemented by an overlay visualisation that colours nodes by average publication year to reveal temporal evolution, and the country co-authorship map applied a minimum of 5 documents per country (Figure 6). A strategic (thematic) map was generated in Bibliometrix to position themes by centrality and density. The key relational indicator throughout is total link strength (TLS), which measures the aggregate strength of a node's co-occurrence or co-citation links.

4. RESULTS

4.1. Publication Trends and Growth Dynamics (RQ1)

Annual scientific production follows a sharply accelerating trajectory, with a compound annual growth rate of 54.15% across the decade. Table 1 and Figure 7 show that output rises steeply and falls naturally into three phases. During the nascent phase (2016-2019), production was low and rose only gradually, from 15 to 38 documents per year, as a small technical community worked on GANs, recommender systems and deepfake detection. An exploration phase (2020-2022) saw modest expansion to 39, 40 and 52 documents, with the first signs of acceleration in 2022 (+30%). The decisive break came in the explosion phase (2023-2025): output jumped to 100 documents in 2023 (+92.3%), surged to 332 in 2024 (+232%) and reached 737 in 2025 (+122%). The single year 2025 accounts for 52.64% of the entire decade's output, and the final 3 years together represent more than 83% of the corpus.

The inflection point coincides precisely with the late-2022 public release of accessible large language models, strongly suggesting that this event, rather than gradual maturation, catalysed the field.

Figure 5: Keyword co-occurrence network and time overlay

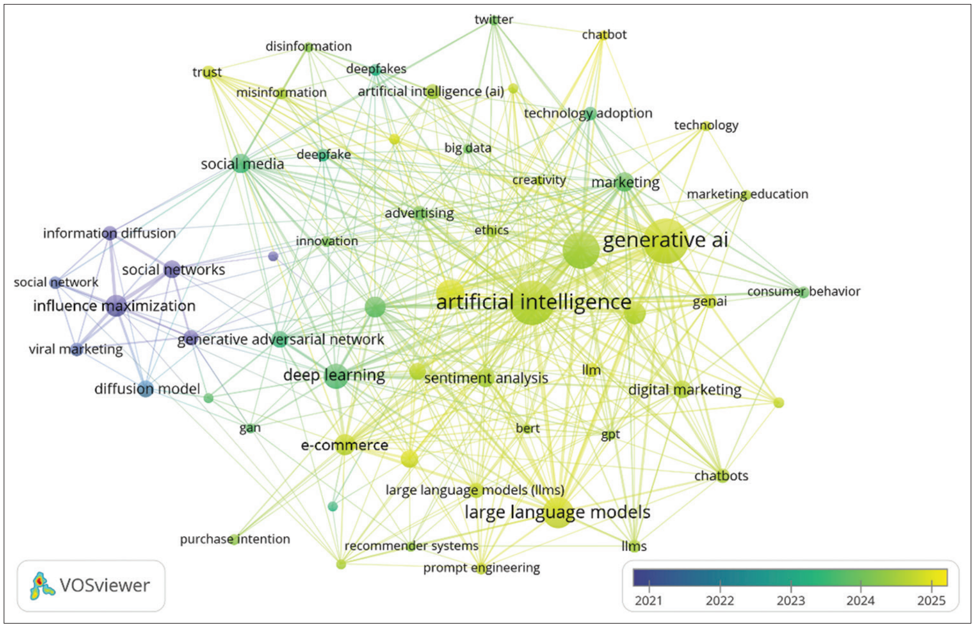
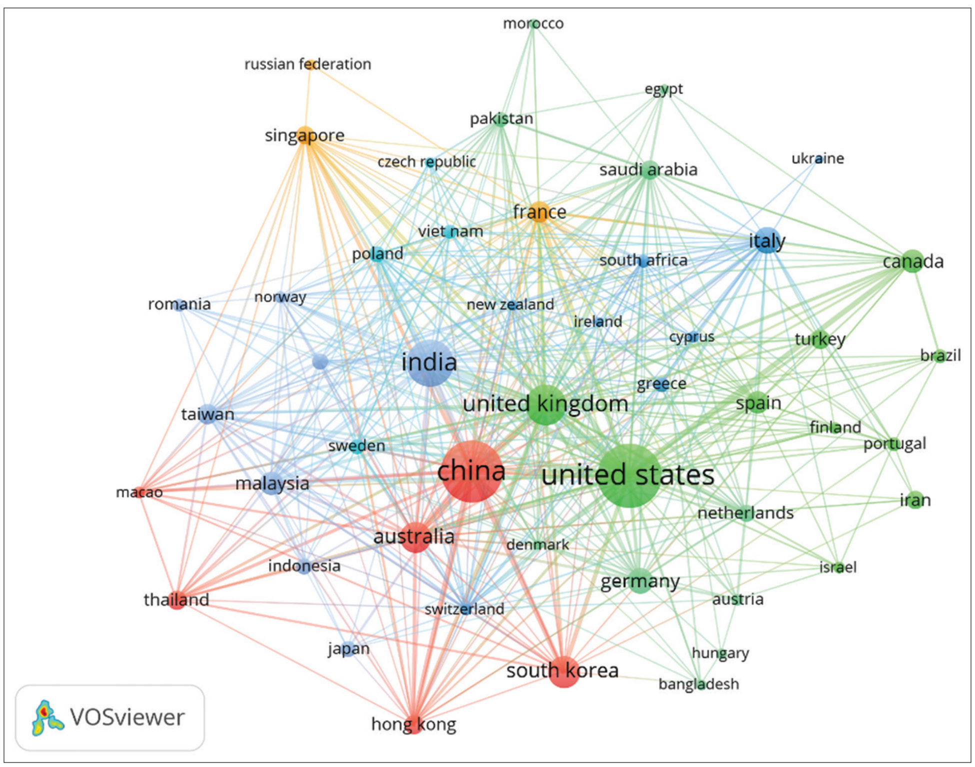


Figure 6: Country co-authorship network (VOSviewer)



Because the search was executed in mid-2026, the 2025 figure is expected to be substantially complete, although minor indexing updates may still occur. The trajectory situates the field firmly in the steep-growth segment of an innovation-diffusion S-curve, with no evidence yet of a plateau.

4.2. Productive and Influential Authors (RQ2)

Table 2 and Figure 8 report the ten most productive author name labels. The list is led by Zhang Y (18 documents), followed by Li Y and Wang Y (17 each), Liu Y (15), Wang S (14) and Wang X (13), with Chen Y, Li J and Wang Z (12 each) and Li X (11) completing the ranking. Two features stand out and must be read together. First, every entry corresponds to a common Chinese surname, consistent with China's position as the most productive country (Section 4.5). Second, and more important, these counts are subject to author-name aggregation. The labels used here are abbreviated surname-plus-initial names rather than disambiguated Scopus Author IDs, and almost certainly conflate multiple distinct researchers, a well-known limitation that is especially severe for high-frequency Chinese surnames. The figures in Table 2 should therefore be read at the author-name-label level, not as evidence of individual super-productivity.

Table 1: Annual scientific production and growth, 2016-2025

Year	Articles (TP)	Cumulative	Share (%)	Annual growth (%)
2016	15	15	1.07	—
2017	23	38	1.64	53.3
2018	24	62	1.71	4.3
2019	38	100	2.71	58.3
2020	39	139	2.79	2.6
2021	40	179	2.86	2.6
2022	52	231	3.71	30.0
2023	100	331	7.14	92.3
2024	332	663	23.71	232.0
2025	737	1400	52.64	122.0

TP: Total publications. Compound annual growth rate over the decade=54.15%

The co-authorship network in Figure 2 tells a complementary and arguably more informative story about the field's social structure. The dominant hub is Dwivedi Y. K., whose node anchors a green cluster (with Kshetri N. and Mogaji E.) and connects to a dense red cluster of marketing and information-systems scholars working substantially in Asian and hospitality contexts, including Ooi K.-B., Tan G. W.-H., Cham T.-H., Aw E. C.-X., Mishra A., Raman R., Cobanoglu C. and Sigala M., alongside smaller blue (Wirtz J., Letheren K.) and yellow (Law R.) groups. The social core of the field is thus organised around a small number of highly visible, well-connected marketing/IS researchers and a cohesive Asian co-authorship community, a structure quite distinct from the fragmented, high-frequency authorship implied by Table 2. Consistent with a young field, author productivity approximates a Lotka-type distribution, in which a few authors account for a disproportionate share of output while most contribute a single document.

Figure 7: Annual scientific production, 2016-2025

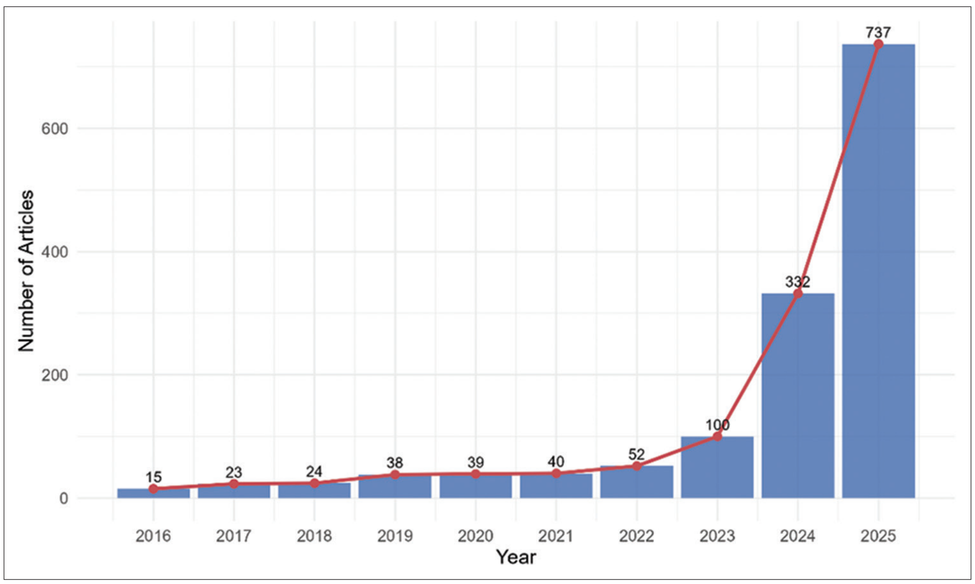
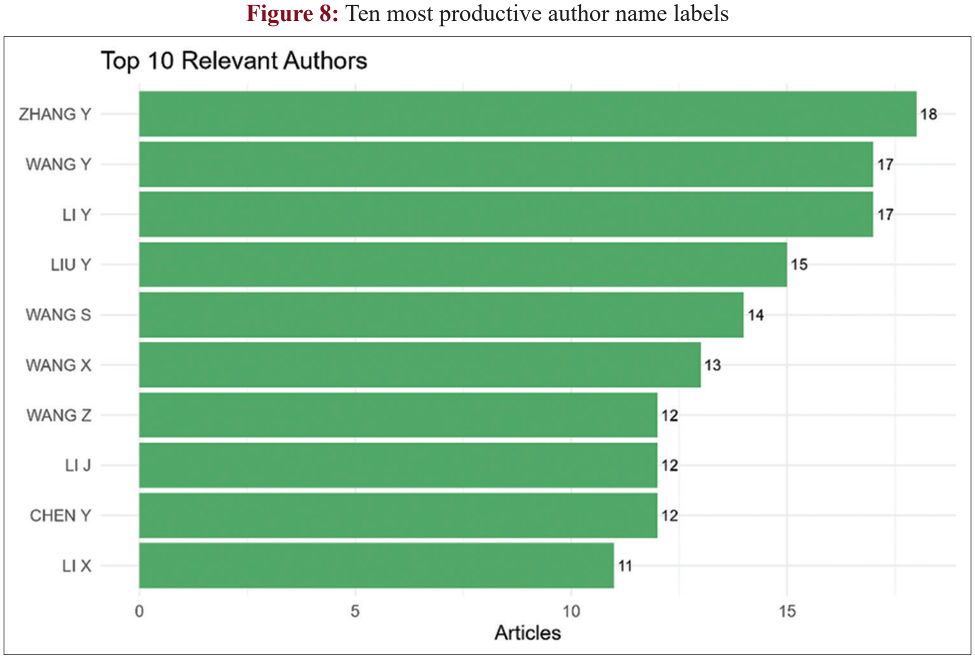


Figure 8: Ten most productive author name labels



4.3. Sources and Intellectual Structure (RQ2)

The publishing landscape (Table 3, Figure 9) blends technical and marketing venues. By volume, the field is led by the computing megajournal IEEE Access (34 documents) and the practitioner outlet applied marketing analytics (20), followed by the Journal of Theoretical and Applied Electronic Commerce Research (18) and a mix of marketing, commerce and multidisciplinary outlets: the Journal of Retailing and Consumer Services (17), Scientific Reports (16), the Journal of Business Research (13), the International Journal of Human-Computer Interaction (10) and Sustainability (10). Strikingly, two marketing-education journals appear in the top ten, Marketing Education Review (12) and the Journal of Marketing Education (9), signalling a vigorous pedagogical sub-conversation about teaching with and about generative AI. The production base therefore spans computing, commerce, consumer research and pedagogy.

Table 2: Ten most productive author name labels

Rank	Author (name-label)	Articles (TP)
1	Zhang Y	18
2	Li Y	17
3	Wang Y	17
4	Liu Y	15
5	Wang S	14
6	Wang X	13
7	Chen Y	12
8	Li J	12
9	Wang Z	12
10	Li X	11

Counts are at the author-name-label level; abbreviated names may aggregate distinct individuals

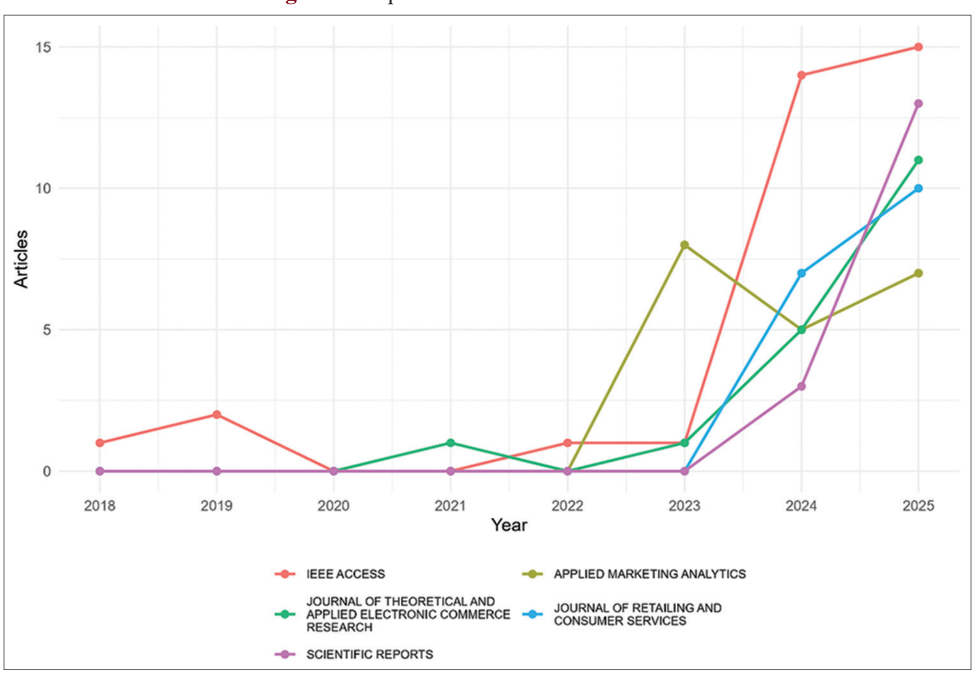
Figure 9 shows how this base shifted over time. IEEE Access carried the field early and sustained its lead, but the marketing and commerce journals rose steeply only in 2024-2025, visual confirmation of a disciplinary migration from computing venues toward marketing venues as the topic matured into a managerial concern. The source co-citation network (Figure 3) reveals a different and more canonical intellectual base. The Journal of Business Research sits at the structural centre, surrounded by a red marketing/IS cluster (with the Journal of Retailing and Consumer Services and the International Journal of Information Management), a blue advertising and consumer-research cluster (Journal of Consumer Research, Journal of Advertising), a green technical cluster (IEEE Access, arXiv, Nature) and a yellow

Table 3: 10 most productive sources

Rank	Source	Articles	Quartile	H-Index	Cite score
1	IEEE Access	34	Q1	338	9.3
2	Applied Marketing Analytics	20	Q3	8	1.5
3	Journal of Theoretical and Applied Electronic Commerce Research	18	Q1	63	7.1
4	Journal of Retailing and Consumer Services	17	Q1	190	24.8
5	Scientific Reports	16	Q1	382	6.4
6	Journal of Business Research	13	Q1	322	22.9
7	Marketing Education Review	12	Q2	20	4.2
8	International Journal of Human-Computer Interaction	10	Q1	110	10.1
9	Sustainability (Switzerland)	10	Q1	207	8.9
10	Journal of Marketing Education	9	Q1	72	8.9

Quartile denotes the journal's best SJR quartile (Scimago); H-Index is the Scimago h-index; CiteScore is the Scopus CiteScore. Metrics reflect the 2025 annual releases (2025 CiteScore from Scopus and 2025 SJR quartile and h-index from Scimago)

Figure 9: Top 5 sources: Production over time



cluster of flagship marketing journals (Journal of Marketing, Journal of Marketing Research, Marketing Science, Journal of the Academy of Marketing Science). In other words, the field publishes substantially in megajournals but draws its intellectual authority from the discipline's flagship outlets.

Document-level impact is highly concentrated (Table 4, Figure 10). The agenda-setting commentary by Dwivedi et al. (2023) dominates with 3,692 citations, more than 1,230 per year, dwarfing all other work. It is followed by Verdoliva's (2020) deepfake overview (766), the cross-disciplinary generative-AI perspective of Ooi et al. (2025; 529, accrued almost entirely within a single year), and a set of technically and conceptually oriented papers, including Blanco-González et al. (2023; 522), Fiore et al. (2019; 516), De Caigny et al. (2018; 476), Peres et al. (2023; 413), Zhao et al. (2024; 320), Gupta et al. (2024; 258) and Campbell et al. (2022; 256). The ranking exposes a dual intellectual base: marketing-native conceptual manifestos (Dwivedi, Peres, Gupta, Campbell, Ooi) coexist with AI/ML methods papers applied to commerce (Verdoliva on deepfakes, Fiore on GAN-based fraud detection, De Caigny on churn, Zhao on LLM recommenders). The appearance of a drug-discovery paper (Blanco-González et al., 2023) among the most-cited documents is a cross-disciplinary spillover, an artefact of the breadth of generative-AI citation, and a reminder that the field's boundaries are porous.

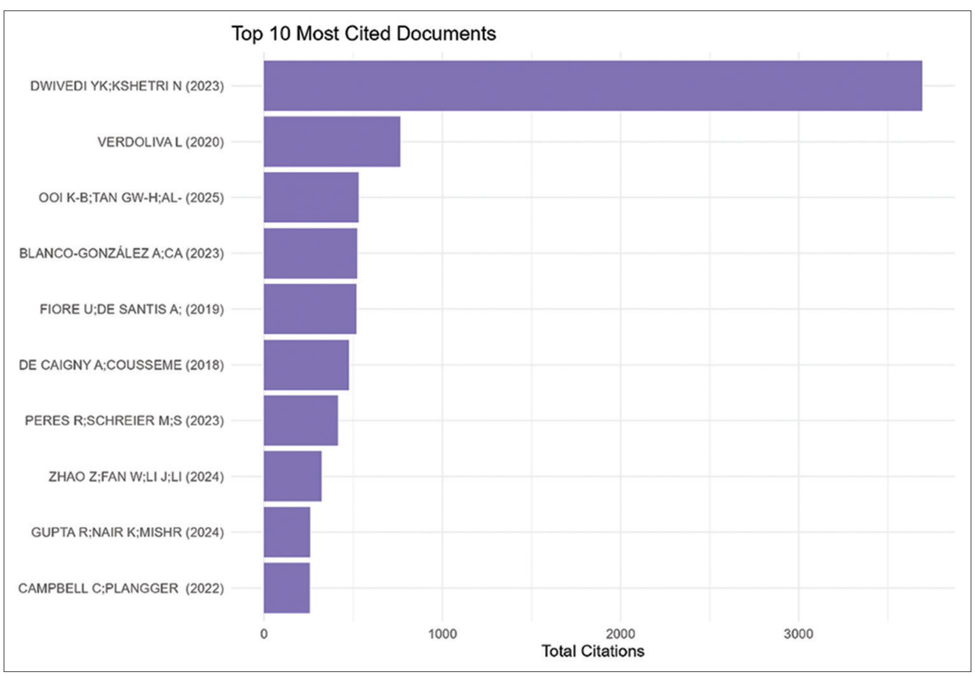
Co-citation of references (Table 5, Figures 4 and 11) makes the field's methodological signature explicit. The single most co-cited reference is Fornell and Larcker (1981), with a total link strength of 3,272, followed by Peres et al. (2023; 2,524), Dwivedi et al. (2023; 2,460), Paul et al. (2023; 2,232), Campbell et al. (2022; 2,086), Ajzen (1991; 2,053), Davenport et al. (2020; 1,990), Gupta et al. (2024; 1,975), Hair et al. (2019; 1,880) and Davis (1989; 1,850). Three intellectual currents are interwoven here: methodological primers for survey-based research (Fornell and Larcker; Hair et al. on PLS-SEM), behavioural technology-adoption theories (Ajzen's theory of planned behaviour; Davis's technology-acceptance model), and recent generative-AI manifestos (Peres, Dwivedi, Campbell,

Table 4: 10 most cited documents

Rank	Authors (abbrev.)	Year	Document (short title)	TC	TC/Year
1	Dwivedi et al.	2023	"So what if ChatGPT wrote it?" Multidisciplinary perspectives on generative conversational AI	3,692	1,230.67
2	Verdoliva	2020	Media forensics and deepfakes: an overview	766	127.67
3	Ooi et al.	2025	The potential of generative AI across disciplines	529	529.00
4	Blanco-González et al.	2023	The role of AI in drug discovery	522	174.00
5	Fiore et al.	2019	Using GANs to improve credit-card fraud detection	516	73.71
6	De Caigny et al.	2018	Hybrid classification for customer-churn prediction	476	59.50
7	Peres et al.	2023	On ChatGPT and beyond: How generative AI may affect research, teaching, practice	413	137.67
8	Zhao et al.	2024	Recommender systems in the era of LLMs	320	160.00
9	Gupta et al.	2024	Adoption and impacts of generative AI: Research agenda	258	129.00
10	Campbell et al.	2022	Preparing for an era of deepfakes and AI-generated ads	256	64.00

TC: Total citations as indexed in Scopus on 6 June 2026, TC/Year: TC divided by years since publication

Figure 10: 10 most cited documents



Davenport, Gupta). The reference co-citation map (Figure 4) positions the Fornell-Larcker node at the structural centre, linking a green methodology-and-adoption cluster (Davis, Ajzen, Sarstedt, Podsakoff, Rogers) to a red marketing-AI cluster (Sorescu, Kietzmann, Niininen, Dennis), a blue NLP/technical cluster (BERT, thematic-analysis methods) and a purple diffusion cluster (Rogers, Bass, influence maximisation). The local view in Figure 11 confirms this methodological reference as the hinge connecting marketing theory with information-systems adoption. This signature, a methodological backbone of SEM and adoption theory carrying a payload of generative-AI conceptual pieces, is a defining and consequential characteristic of the field, to which the Discussion returns.

Table 5: 10 most co-cited references

Rank	Co-cited reference	TLS	Role in the knowledge base
1	Fornell and Larcker (1981)	3,272	SEM measurement/ methodology primer
2	Peres et al. (2023)	2,524	Generative-AI marketing manifesto
3	Dwivedi et al. (2023)	2,460	Multidisciplinary generative-AI agenda
4	Paul et al. (2023)	2,232	Review-methodology/ agenda reference
5	Campbell et al. (2022)	2,086	Deepfakes and AI-generated advertising
6	Ajzen (1991)	2,053	Theory of planned behaviour (adoption)
7	Davenport et al. (2020)	1,990	AI and the future of marketing
8	Gupta et al. (2024)	1,975	Generative-AI adoption theory
9	Hair et al. (2019)	1,880	PLS-SEM methodology primer
10	Davis (1989)	1,850	Technology-acceptance model (adoption)

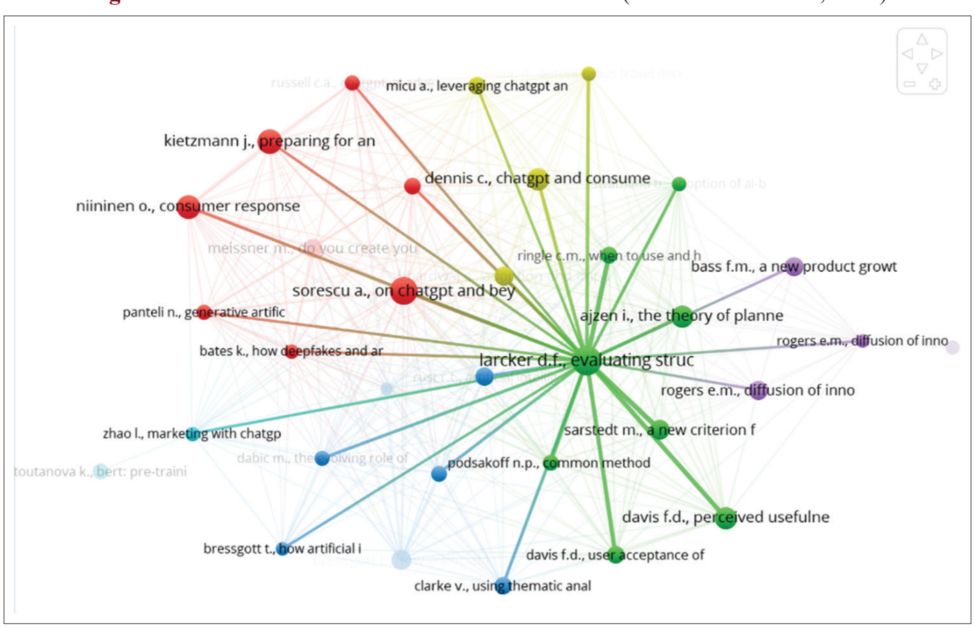
TLS: Total link strength from the cited-reference co-citation network, computed with the bibliometrix R package over all cited references; Figure 4 visualises this network in VOSviewer at a 15-citation threshold for readability

4.4. Conceptual Structure and Thematic Evolution (RQ3)

Author-keyword analysis (Figures 12 and 13) confirms a lexical core organised around generative AI (the single most frequent keyword, with 203 occurrences), followed by artificial intelligence (194), ChatGPT (136), large language models (94), generative artificial intelligence (80), deep learning (61) and machine learning (46). The persistence of deep- and machine-learning terms alongside the generative vocabulary is itself a finding: it shows that the technical substrate of the pre-2022 era remains embedded in the field's language even as generative terms come to dominate. The word cloud (Figure 12) adds the surrounding semantic field (social media, influence maximisation, sentiment analysis, natural-language processing, e-commerce, advertising, deepfakes, trust, prompt engineering, purchase intention and technology adoption), sketching the bridge between technical methods and managerial outcomes.

The keyword co-occurrence network (Figure 5) resolves this semantic field into five communities: a generative-AI marketing core (generative AI, artificial intelligence, marketing, digital marketing, chatbots, consumer behaviour); an algorithmic-distribution cluster (influence maximisation, social networks, generative adversarial networks, diffusion models, viral marketing, information diffusion, e-commerce); an LLM/NLP cluster (large language models, GPT, BERT, sentiment analysis, prompt engineering, recommender systems, purchase intention); a responsible-governance cluster (deepfakes, misinformation, disinformation, fake news, trust, ethics); and a smaller adoption bridge (chatbot, technology adoption, innovation). The temporal overlay (Figure 5, time-coloured) and the keyword-growth curves (Figure 14) show a clear hand-off. The older distribution-and-technical terms (influence maximisation, social networks, diffusion, GANs) grow early and steadily before being overtaken, while generative AI, ChatGPT, LLMs and prompt engineering remain near-zero until 2022-2023 and then rise almost vertically. Critically, ethics-, trust- and misinformation-related terms migrate

Figure 11: Local view of the central co-cited reference (Fornell and Larcker, 1981)

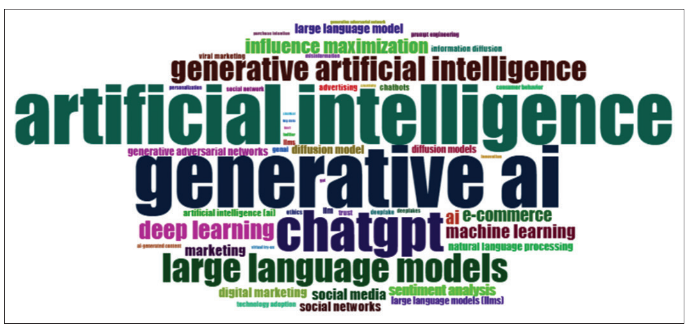


toward the centre of the network in the most recent period, indicating that responsible-governance concerns are becoming structural rather than peripheral.

The strategic (thematic) map (Figure 15) integrates these observations along the axes of centrality and density. The motor themes (well developed and central) comprise a social-media/deepfake/misinformation theme and an artificial-intelligence/ChatGPT/generative-AI theme, confirming that synthetic-media risk has joined generative text at the heart of the field. The basic themes (central but still developing) are a generative-AI/large-language-models/digital-marketing theme and a deep-learning/machine-learning/e-commerce theme, which function as transversal foundations. The niche themes (specialised but peripheral) include topic modelling/metaverse/virtual reality and an AI-generated-content/deepfakes cluster. Finally, the emerging-or-declining quadrant holds two distinct groups: Trust/purchase intention/privacy, which are emerging consumer-outcome concerns, and influence maximisation/social networks/diffusion models, which are declining as standalone topics inherited from the technical era.

Synthesising the network and strategic analyses, the field can be organised into four coherent themes. (1) Content production (the generation of text and, less prominently, images through LLMs, prompt engineering and generative models) is the field's centre of gravity. (2) Distribution channels (social networks, recommender systems, influence maximisation and diffusion) form the legacy-technical core, now maturing and partly declining as a standalone theme while feeding the others. (3) Audience reach (consumer behaviour, purchase intention, engagement, sentiment, authenticity and adoption) represents the emerging consumer-outcome focus. (4) Responsible governance (deepfakes, misinformation, ethics, privacy and trust-as-risk) is moving decisively from the periphery toward the motor quadrant. This four-theme structure provides an integrative organising frame for a literature that is otherwise fragmented across disciplines.

Figure 12: Author-keyword word cloud

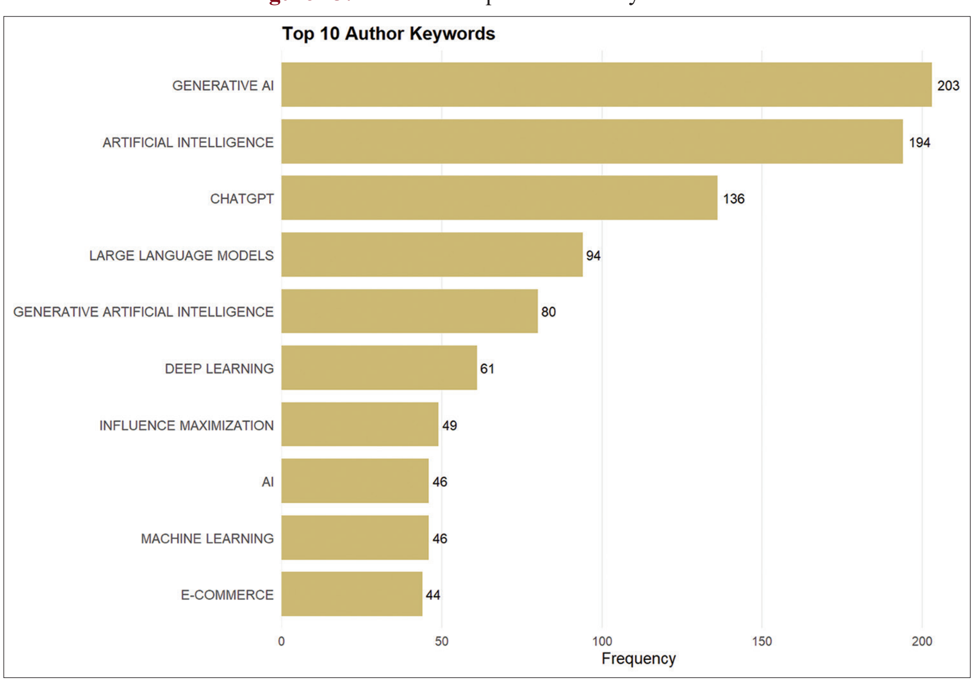


4.5. Geographic Distribution and Collaboration (RQ4)

Production is geographically concentrated yet globally connected (Figure 16). China leads with 652 documents, narrowly ahead of the United States (591); India is a clear third (334), followed by the United Kingdom (212), Korea (132), Australia (122), Italy (102), Germany (76), Malaysia (68) and Spain (65). Country output is counted at the document level under full counting, with each document credited to every country appearing in its author affiliations; because international co-authorship is common, country totals therefore sum to well above the 1400 documents. Two observations stand out. First, the field rests on a United States–China dual core that together far outweighs any other contributor. Second, India's strong third place is notable for an applied-marketing field; it reflects the country's large information-systems and computing research base and its substantial English-language output. The presence of Malaysia in the top ten is similarly noteworthy and consistent with the cohesive Asian co-authorship community identified in Figure 2.

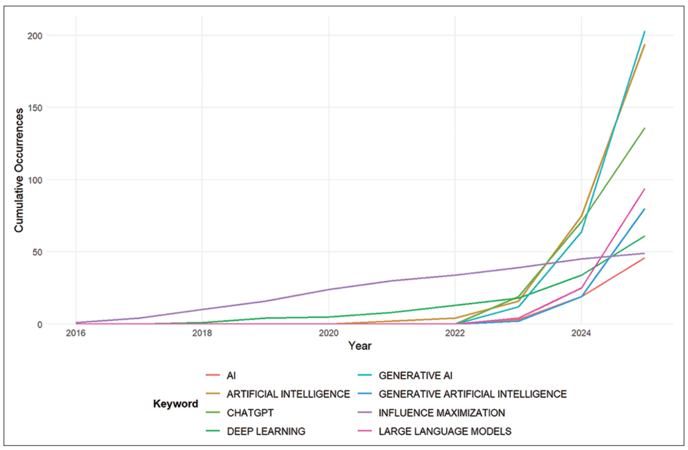
The country co-authorship network (Figure 6) shows that this concentration does not imply bipolarity in collaboration. Four

Figure 13: Ten most frequent author keywords



regional clusters are visible: A green Western cluster (United States, United Kingdom, Italy, Germany, Canada, Spain, Netherlands and many European and Middle-Eastern partners); a red East-Asian and Oceanian cluster (China, Australia, South Korea, Hong Kong, Macao, Thailand, Japan); a blue South-Asian cluster (India and Malaysia, with several smaller partners); and an orange Francophone-Singaporean bridge (France, Singapore, with Russia, Poland and Vietnam). The United States and China are the largest and most-connected nodes, but India functions as a structural bridge linking the Western and East-Asian communities. The field is therefore genuinely global in collaboration while organised along regional lines: the United States and China anchor its principal hubs, while India provides the connection between its Western and East-Asian poles.

Figure 14: Cumulative keyword growth over time



4.6. The AIGC Tool Landscape: A Text-Centric Field (RQ4)

A distinctive contribution of this study is a tool-level analysis of which AIGC technologies the literature discusses (Figures 17 and 18). The distribution is extraordinarily skewed toward text. ChatGPT is mentioned in 277 documents and the broader GPT family (GPT-3/4 and related series) in 250; because many documents reference both, these correspond to 322 distinct documents, dwarfing every other tool. Conversational and large-language-model tools therefore account for most of the tool-level attention. By contrast, image generators are marginal (Stable Diffusion 12, DALL-E 10, Midjourney 9, summing to just 31), video generation is negligible (Sora 4), synthetic-video and avatar tools barely register (Synthesis 1), and dedicated marketing-copy tools are essentially absent from the scholarly record (Jasper 0). The temporal view reinforces the pattern: ChatGPT and GPT rise from near-zero in 2022 to roughly 100 and 95 documents in 2024 and 148 and 130 in 2025, while image and video tools scarcely lift off the horizontal axis.

The implication is clear and, to our knowledge, undocumented in prior reviews: research on AIGC in digital marketing has so far been overwhelmingly text-centric, effectively equating AIGC with conversational text generation. The marketing consequences of AI-generated images, video and synthetic spokespeople (arguably the most visible forms of brand content) remain comparatively under-studied. This asymmetry is one of the field's clearest white spaces and a concrete priority for future work.

Figure 15: Strategic diagram of themes by centrality and density

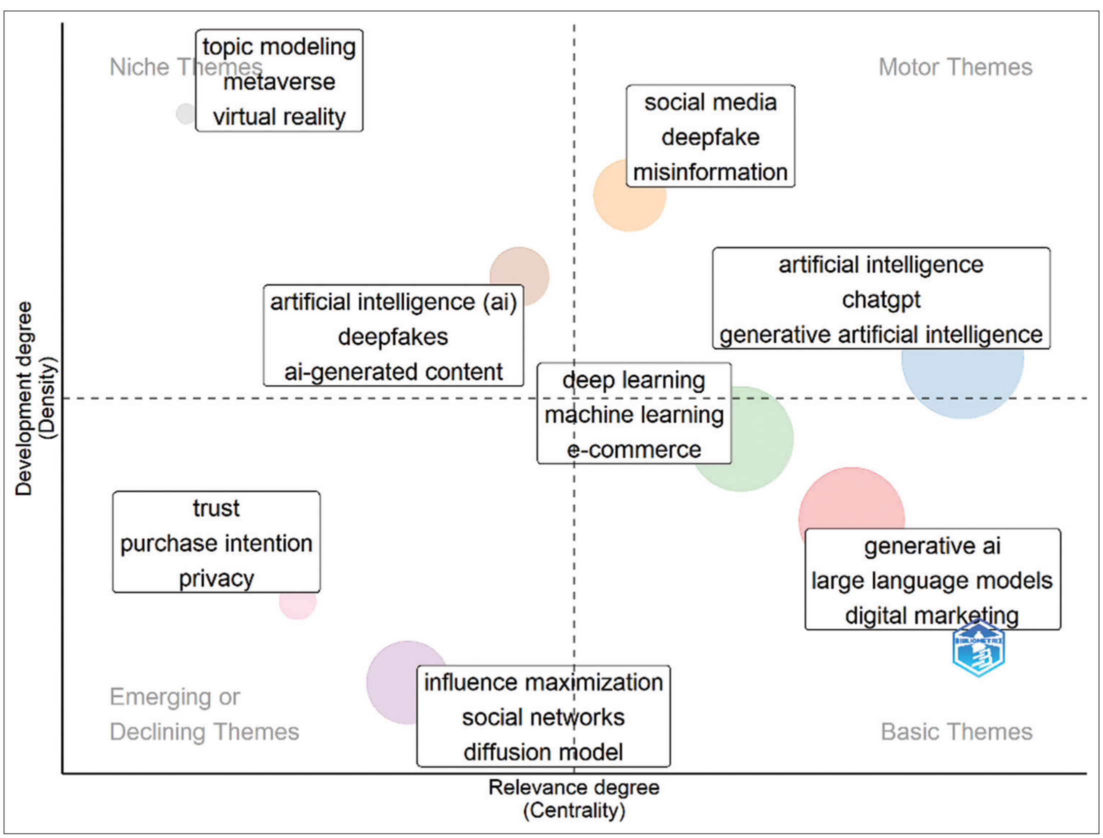


Figure 16: Top 10 countries by publication output

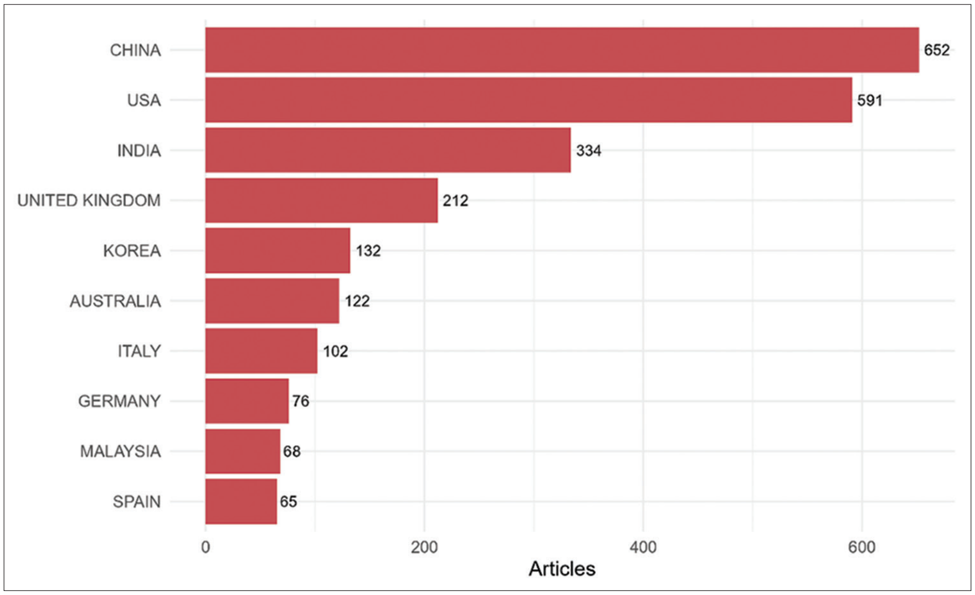
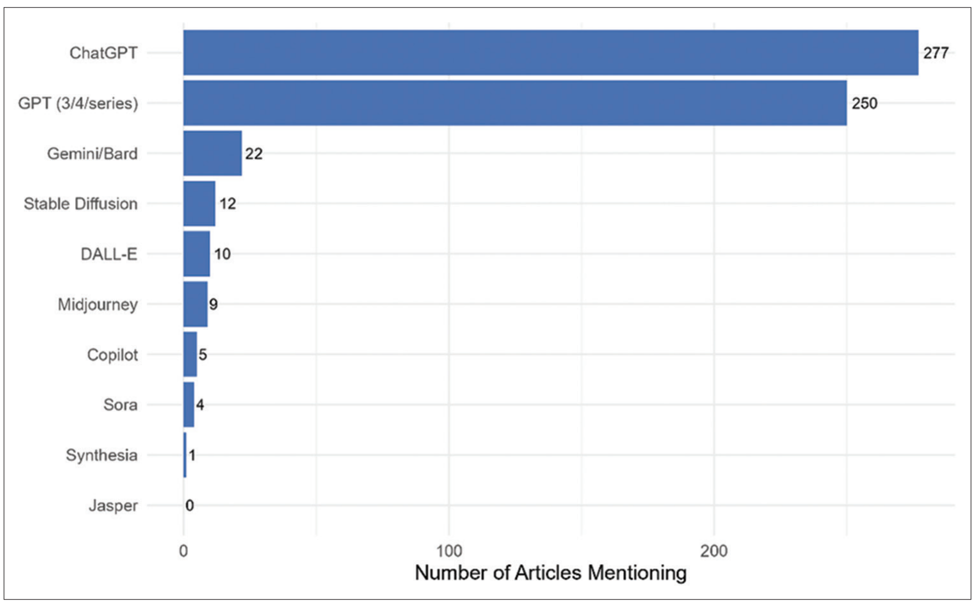


Figure 17: AIGC tool mentions across the corpus



4.7. Platform Coverage and the Asian-Platform Gap (RQ4)

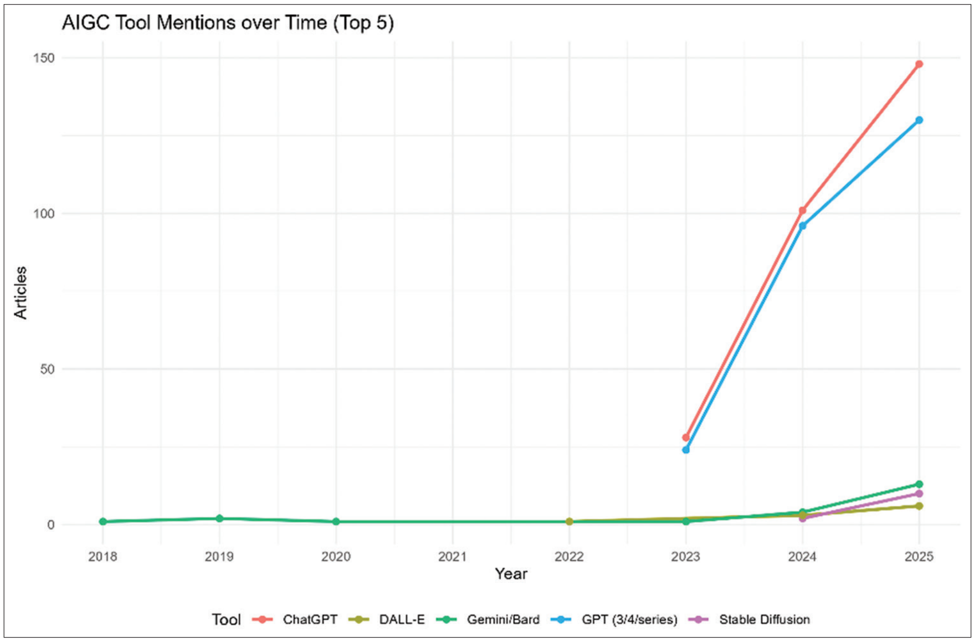
A parallel analysis of named social platforms is more tentative but equally revealing. Platform-specific study is thin in absolute terms (the field theorises AIGC and consumer response more often than it grounds them in particular platforms), and within that thin literature attention concentrates on Western platforms. Instagram (18 mentions), YouTube (16) and Facebook (12) together account for 46 mentions, whereas the major Asian platforms TikTok (6), Weibo (5), Xiaohongshu (1), WeChat (1) and Line (0) together account for only 13. Because these absolute counts are small, the result is best read not as a headline finding but as a clearly identified white space. Even so, the asymmetry is striking: The most productive country in the field, China, anchors precisely the platform ecosystem that the literature studies least. This mismatch between where research is produced and which platforms it examines is itself an underexplored tension and a priority for future, geographically grounded research.

5. DISCUSSION

5.1. Theoretical Interpretation

The growth trajectory documented in Section 4.1 is well described by the diffusion-of-innovations perspective (Rogers, 2003): A long, flat introduction during the technical pre-history; a sharp take-off triggered by the public availability of accessible generative models in late 2022; and a steep-growth phase that, as of 2025, shows no sign of saturation. In diffusion terms, the field is still in a steep, pre-saturation phase. The tool findings can be read through the strategic-AI lens of Huang and Rust (2021): scholarship has concentrated on the "thinking" and increasingly "feeling" capabilities embodied

Figure 18: The top five AIGC tools over time



in conversational text systems, while the creative, visual frontier of image and video generation has attracted far less theoretical attention, mirroring the empirical asymmetry in tool mentions.

The co-citation backbone identified in Section 4.3 carries an important theoretical message. The field has imported consumer-information-systems adoption theory, namely the technology-acceptance model (Davis, 1989) and the theory of planned behaviour (Ajzen, 1991), wholesale, scaffolded by structural-equation methodology (Fornell and Larcker, 1981; Hair et al., 2019). This has been productive, supplying ready constructs and validated instruments for a new phenomenon. Yet it also risks a theoretical monoculture. Adoption-intention models were designed to explain whether users accept a given technology; they are less suited to the questions AIGC most sharply raises: creativity, co-production, authenticity, and the reconfiguration of marketing capabilities. There is room, accordingly, for dynamic-capabilities and service-dominant-logic perspectives, for theories of creativity and authenticity, and ultimately for constructs developed natively for generative contexts rather than borrowed from earlier technology waves. Tellingly, an experiential perspective on consumers and AI already exists (Puntoni et al., 2021), yet it does not appear among the field's most co-cited references (Table 5), indicating that the literature under-uses the non-adoption theory already available to it.

5.2. Methodological Reflection

The same co-citation evidence points to a methodological concentration. The prominence of measurement and common-method references alongside PLS-SEM primers indicates heavy reliance on cross-sectional, survey-based designs that model self-reported intentions. Such designs are valuable for early theory-testing but are limited for establishing the actual behavioural and market effects of AIGC. Despite the field's technical heritage, experimental, field-experimental, longitudinal and behavioural-trace studies remain comparatively scarce, as does work that uses computational or explainable-AI methods to interrogate generative systems directly. Moving the field from intention to demonstrated effect will require a broader methodological repertoire, including controlled experiments and analyses of real consumer behaviour. Noy and Zhang's (2023) controlled experiment on the productivity effects of generative AI, published in Science, exemplifies the kind of causal design that the marketing-specific literature still rarely adopts.

5.3. Positioning Relative to Prior Reviews

This study extends a small but growing set of reviews of generative AI in marketing. Comparable syntheses are typically bounded to the post-2022 period and to corpora of a few hundred documents (for example, Prasanna and Kushwaha, 2025, 371 documents; Pushparaj et al., 2025, 182 documents; Panda et al., 2026, 134 documents). The present decade-scale analysis of 1400 documents makes three contributions that narrower reviews cannot. It recovers the pre-ChatGPT technical foundations (GANs, recommender systems and deepfake detection) and demonstrates their continuing imprint on the field's vocabulary and reference base. It documents, at tool level, the pronounced asymmetry between text generation and visual generation in scholarly attention. Even the rare studies that bridge the two modalities, such as Wahid et al. (2023), which pairs ChatGPT with Midjourney for content marketing, remain isolated exceptions that underscore rather than close this gap. And it surfaces a geography-platform mismatch: A heavily Asian production base studying a heavily Western platform set. These contributions complement rather than contradict existing reviews, situating the generative surge within a longer historical arc and a finer-grained empirical map.

5.4. Limitations

Several limitations qualify the findings. First, reliance on a single database (Scopus) ensures metadata consistency but omits venues indexed only elsewhere (for example, in Web of Science, IEEE Xplore or the ACM Digital Library), so coverage of some technical and very recent work is partial. Relatedly, the deliberately broad query, designed to capture the field's technical pre-history (including work on generative adversarial networks and deepfake detection), admitted a small number of cross-disciplinary spillover records, most visibly a highly cited drug-discovery paper. These were retained only where genuinely co-cited within the corpus and are explicitly flagged as such (Section 4.3), so they do not distort the core structural findings. Second, the restriction to English-language journal articles and reviews excludes conference proceedings, an important channel in computing, and non-English scholarship; this probably undercounts both technical contributions and Chinese-language research. Third, author-name aggregation means that the productivity counts in Table 2 are at the name-label level and may conflate distinct individuals, an issue most acute for common surnames. Fourth, the tool and platform analyses rely on term frequency in titles, abstracts and keywords, which approximates but cannot perfectly capture the technologies a study actually engages, and tends to undercount works that discuss tools without naming them. Finally, the sparse early-period record (2016-2019) reflects genuine field youth rather than a data defect, so structures inferred for those years are indicative.

5.5. Directions for Future Research

The map points to a structured agenda. First, research should move decisively beyond text to examine the marketing effects of AI-generated images, video and synthetic spokespeople, the field's clearest white space. Second, it should strengthen causal evidence through experiments, field trials and longitudinal designs that measure actual consumer behaviour rather than stated intentions. Third, it should broaden its theoretical base toward dynamic capabilities, value co-creation, and creativity and authenticity theory, developing constructs native to generative contexts. Fourth, it should study Asian platforms and multilingual, multi-market contexts so that empirical attention matches the geography of production. Fifth, because the thematic map shows responsible-governance concerns becoming structural, future work should integrate transparency, AI-use disclosure, provenance and deepfake detection into mainstream marketing models. Sixth, multi-database and multilingual replications would test the robustness of the present map.

6. CONCLUSIONS AND IMPLICATIONS

This study mapped a decade of research at the intersection of AI-generated content and digital marketing, using a PRISMA-screened corpus of 1400 Scopus-indexed documents (2016-2025). The field has grown explosively, at a compound annual rate exceeding 54%, through three phases, with the late-2022 arrival of accessible large language models marking a decisive take-off and 2025 alone accounting for more than half of all output. Production rests on a United States-China dual core, bridged by India and organised into regional collaboration clusters. Intellectually, the field fuses a methodological backbone of adoption theory and structural-equation modelling with a payload of recent generative-AI manifestos, and it can be organised into four themes (content production, distribution channels, audience reach and responsible governance), the last of which is migrating from the periphery toward the core.

Two findings are particularly consequential. The literature is overwhelmingly text-centric, equating AIGC with conversational text generation and leaving AI-generated images and video comparatively unexamined; and there is a mismatch between the field's heavily Asian production base and its heavily Western platform focus. Both represent clear opportunities for future research and for practice. By recovering the field's technical foundations, descending to tool level, and attending to geography and platform, this decade-scale map offers researchers an integrative frame and a concrete agenda, and offers managers an evidence-based orientation to a fast-moving domain. As generative technologies continue to advance, periodic re-mapping will be valuable to track whether the field broadens beyond text, balances its geographic attention, and develops the native theory the phenomenon demands.

The findings carry direct implications for marketing managers, platform strategists and educators.

Industrialise content production responsibly. Generative tools substantially reduce the marginal cost of producing draft marketing content, making large-scale, personalised content far more economically feasible. To capture this value without eroding brand equity, firms should pair automation with editorial governance: human-in-the-loop review, brand-voice guidelines and factual-accuracy checks, so that scale does not come at the expense of quality, consistency or accuracy.

Mind the text-first reality and seize the visual frontier. The evidence base has developed far more rapidly around text generation than around AI-generated images and video. For managers this is at once a risk (evidence-based guidance on visual AIGC is scarce) and a first-mover opportunity. Brands willing to experiment carefully with AI-generated visual and video content, while monitoring consumer response, may gain advantage ahead of settled best practice.

Make platform strategy region aware. Because the evidence base skews toward Western platforms, managers operating on Asian platforms such as TikTok/Douyin, Weibo, Xiaohongshu and WeChat are working with thinner research support. Findings derived from Western platforms should not be assumed to transfer; localised testing and platform-specific measurement are warranted, particularly given the strategic importance of these ecosystems in Asian digital commerce.

Treat trust, authenticity and disclosure as strategy, not compliance. With deepfakes and misinformation now among the field's motor themes, the management of authenticity has become central. Proactive disclosure of AI use, provenance signalling for synthetic media, and investment in detection capability are increasingly strategic differentiators that protect consumer trust, rather than mere regulatory obligations.

Build organisational capability and skills. The prominence of marketing-education outlets among the field's most productive sources underscores a workforce-capability gap. Firms and educators should prioritise prompt literacy, oversight and editorialjudgement skills, and AI-governance competencies, so that human marketers can direct and supervise generative systems effectively rather than be displaced by them or over-reliant on them.

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APPENDIX A: SCOPUS SEARCH QUERY

The following query reproduces the search strategy executed in Scopus in 2026. Terms are combined within TITLE-ABS-KEY; the "brand*" term generated a small number of "brand new" false positives that were removed during manual screening.

(TITLE-ABS-KEY ("aigc" OR "ai-generated content" OR "generative ai" OR "generative artificial intelligence" OR "large language model*" OR "llm*" OR "chatgpt" OR "gpt-*" OR "text-to-image" OR "text-to-video" OR "diffusion model*" OR "generative adversarial network*" OR "gan" OR "foundation model*" OR "multimodal generative*" OR "midjourney" OR "dall-e" OR "dalle" OR "stable diffusion" OR "sora" OR "gemini" OR "copilot" OR "synthesia" OR "jasper ai" OR "image generation" OR "ai-generated image*" OR "ai-generated video*" OR "synthetic media" OR "deepfake*"]) AND (TITLE-ABS-KEY ["marketing" OR "advertis*" OR "brand*" OR "consumer behavio*" OR "consumer engagement" OR "customer engagement" OR "e-commerce" OR "ecommerce" OR "social commerce" OR "influencer*" OR "purchase intention*" OR "word-of-mouth" OR "endorsement*" OR "marketing communication*"]) AND PUBYEAR >2015 AND PUBYEAR <2026 AND (LIMIT-TO [DOCTYPE, "ar") OR LIMIT-TO [DOCTYPE, "re"]) AND (LIMIT-TO [LANGUAGE, "English"]). The asterisk (*) denotes truncation for spelling and morphological variants.