



AI-ENABLED PARTICIPATORY MARKETING: A BIBLIOMETRIC ANALYSIS AND RESEARCH AGENDA

Wachiranun Pum	Technology of Information System Management Division, Faculty of Engineering, Mahidol University, Nakhonpathom, Thailand	wachiranun.pum@outlook.com
Narongsak Sukma	Faculty of Digital, Siam Technology College, Bangkok, Thailand	narongsaks@siamtechno.ac.th
Adisorn Leelasantitham*	Technology of Information System Management Division, Faculty of Engineering, Mahidol University, Nakhonpathom, Thailand	adisorn.lee@mahidol.ac.th

* Corresponding author

ABSTRACT

Aim/Purpose	This study addresses the structurally skewed measurement of performance outcomes in the rapidly expanding AI-enabled participatory marketing literature. This paper aims to map the intellectual structure of this field, to measure the amount of outcome-related research in six performance domains and to identify the gaps that should guide the next cycle of empirical investment for the field.
Background	This fragmentation makes it harder to compare studies, carry out meta-analytic synthesis, and for practitioners to predict what outcome dimensions will be most reliably influenced by investments in AI marketing. Bibliometric analysis offers a reproducible, data-driven tool for unlocking the structural distribution of this research in an expanding, technology-intensive corpus.
Methodology	Following a three-stage sequential screening process (criteria: publication date 2015 or later; peer-review status; and substantial treatment of AI marketing or participatory marketing outcomes), a final corpus of 467 records (2015–2026) was constructed. We applied four complementary bibliometric methods: 1. publication trend analysis; 2. source and author analysis; 3. keyword co-occurrence network analysis; and 4. performance outcome mapping protocol with domain-specific lexicons.

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Contribution	This paper aims to provide the following: (1) what is, to the authors' knowledge, the first comprehensive bibliometric map of AI-enabled participatory marketing research organized around a six-domain performance outcome framework; (2) a quantitative distribution of outcome coverage revealing overrepresented areas (efficiency: 40.3%; stakeholder trust: 38.5%) and a critical empirical gap (market reach: 8.4%); and (3) a six-direction research agenda based on bibliometric evidence rather than researcher judgment to rebalance the field's methodological portfolio.
Findings	Five thematic clusters were identified (% of 467-paper corpus; multi-assignment permitted): AI and Data Infrastructure (37.3%); Digital Marketing Strategy (33.0%); Stakeholder and Participatory Engagement (58.9%); Organizational Dynamics and Leadership (30.0%); and Performance and Competitive Outcomes (60.0%). The corpus grew at a CAGR of 23.3% (2015-2024), with a YoY growth of 192.6% in 2024.
Recommendations for Practitioners	AI marketing managers should prioritize the following: (1) longitudinal measurement frameworks that track ROI and competitive advantage over 3–5 year cycles; (2) GIS-enabled and cross-national market reach metrics as primary KPIs, not secondary correlates; (3) context-adapted AI deployment models for emerging-market settings; (4) systematic adverse-outcome monitoring protocols (privacy, algorithmic bias, stakeholder exclusion); (5) an integrated AI Marketing Performance Index (AMPI) encompassing all six outcome domains; and (6) multi-group analysis of industry and firm-size boundary conditions before scaling AI marketing investment.
Recommendations for Researchers	Priorities are (1) longitudinal panel designs that track competitive advantage over a 3-5 year period; (2) market reach as the primary dependent variable using GIS and cross-national instruments; (3) studies of the emerging market context with adapted measurement instruments; (4) negative outcome and failure-mode studies; (5) an integrated AI Marketing Performance Index; and (6) moderator studies using multi-group structural equation modelling.
Impact on Society	As AI marketing systems scale globally, their structural bias toward documenting best-case performance scenarios while ignoring adverse outcomes – privacy breaches, algorithmic bias, stakeholder exclusion – has direct societal consequences. The research agenda proposed here seeks to produce corrective evidence that supports equitable and transparent AI governance in marketing contexts. For the informing science and knowledge management community, these findings underscore the urgency of developing structured, multi-domain performance frameworks that can distinguish value creation from value extraction in AI-intensive environments.
Future Research	Six directions are proposed. Most urgent are studies of longitudinal competitive advantage, market reach as primary outcome, and systematic mapping of negative/paradoxical outcomes. Medium term priorities are integrated performance index and cross national emerging market studies. With the corpus going beyond 250 annual publications, computational text analysis and co-citation network analysis should be based on this bibliometric base.
Keywords	AI-enabled marketing, participatory marketing, bibliometric analysis, performance outcomes, market reach, stakeholder trust, co-creation, research agenda, knowledge management

INTRODUCTION

Of the 467 studies published on AI-enabled participatory marketing — defined here as the use of AI systems within governance structures that actively incorporate diverse stakeholder inputs into marketing decision-making (“participatory”) — from 2015 to 2026, more than 40% focused on operational efficiency, while fewer than 9% examined whether AI marketing systems genuinely extend a firm’s market reach. This imbalance — the over-representation of efficiency outcomes and the near-absence of market reach evidence — does not appear to reflect theoretical prioritization. A plausible explanation is methodological accessibility: efficiency can be measured within a single cross-sectional survey, whereas market reach requires longitudinal, geographic, and multi-stakeholder data that most individual studies cannot afford to collect. Confirming this explanation, however, requires systematic bibliometric analysis — the task this paper undertakes. The result is a literature that documents with reasonable precision what AI marketing does to existing operations, but not what it makes possible beyond them.

The problem is compounded by the field’s growth trajectory. Publications indexed in Scopus on AI, participatory governance and marketing technology have had a compound annual growth rate (CAGR) of 23.3% over the observed period 2015-2024, with a year-on-year surge of 192.6% in 2024 as the large language model deployment in commercial marketing contexts is widely normalized (Davenport et al., 2020; Grewal et al., 2020). This rate of growth places the domain among the most rapidly growing areas of research in management science (Lamberton & Stephen, 2016) and creates both opportunity and risk: opportunity, because an expanding literature provides an empirical base on which to build theory, and risk, because rapid growth without structural coordination produces methodological fragmentation and measurement pluralism (Donthu et al., 2021; Zupic & Cater, 2015). One such outcome is the scattering of performance outcome constructs—efficiency, innovation, market reach, stakeholder trust, competitive advantage, co-creation—across theoretical traditions with no shared operationalization (Morgan, 2012; Vorhies & Morgan, 2005). What the field needs is a quantitative intellectual map of which outcome dimensions have been sufficiently empirically invested in and which have not. In the context of knowledge management, Mooradian (2024) argues that AI-intensive domains require systematic and evidence-based approaches to structuring knowledge that go beyond the interpretation of individual researchers.

Bibliometric analysis is the method best suited to this task (Donthu et al., 2021; Paul & Criado, 2020). Bibliometric approaches use quantitative methods on publication metadata to map the intellectual structure of a field — what topics co-occur, what streams of knowledge converge and where are there structural gaps. The default first-stage method in fast-growing, technology-intensive research fields is bibliometric mapping precisely because it can unveil the distribution of a literature’s empirical priorities without the confirmation bias imported by qualitative reviews through their choice of focal papers (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010).

This study focuses on three research questions.

RQ1: What is the intellectual structure of AI-enabled participatory marketing research based on bibliometric analysis of 467 publications indexed in Scopus during the period 2015-2026?

RQ2: What are the most and least represented performance outcome constructs in the corpus and what does this distribution tell us about the empirical priorities of the field?

RQ3: What are the structural gaps in the outcomes research and what future research directions will most productively advance the empirical foundation of the field?

The intersection of AI systems, participatory governance structures, and performance outcome measurement constitutes a distinct analytical domain for three reasons. First, AI marketing and participatory marketing make competing theoretical predictions about who captures value: efficiency-centric AI marketing models predict firm-side gains, while participatory co-creation models predict multi-

stakeholder value distribution. Resolving this tension requires outcome evidence that maps across both dimensions simultaneously. Second, the rapid growth of this literature (CAGR = 23.3%) means that without a structural map, fragmentation compounds faster than synthesis can occur. Third, performance outcomes in this intersection are not reducible to either general AI marketing metrics or general co-creation metrics; the participatory dimension introduces governance complexity that demands its own empirical framework. These three reasons justify treating AI-enabled participatory marketing as a domain worthy of dedicated bibliometric investigation, rather than a subset of broader AI marketing research. Three contributions follow. First, we present what is, to the authors' knowledge, the first bibliometric map of the AI-enabled participatory marketing literature organized around a six-domain performance outcome framework — a framework that makes the field's empirical priorities directly visible and comparable. Second, we quantify the distribution of outcome coverage, showing that market reach (8.4%) represents a critical empirical gap despite being a primary business rationale for AI marketing investment. Third, we propose a six-direction research agenda grounded in bibliometric evidence rather than individual researcher judgment. Previous bibliometric work has taken a wide view of the use of AI in business (Dwivedi et al., 2021) and digital marketing strategy (Kannan & Li, 2017); this work maps the intersection between AI technology and participatory governance specifically and applies a performance outcome mapping protocol that has not been previously used at this intersection. The theoretical background is presented in the next section, the methodology is described in the third section. The fourth section reports the results, and the discussion is developed in the fifth section. The last section presents the conclusion..

THEORETICAL BACKGROUND

DEFINING AI-ENABLED PARTICIPATORY MARKETING

Before surveying the theoretical landscape, it is necessary to set the boundary conditions of the construct. AI-enabled participatory marketing is defined as the use of AI tools — machine learning systems, natural language processing, and predictive analytics platforms — within governance structures that actively incorporate diverse stakeholder inputs (consumer preferences, employee feedback, and community data) into system training, refinement, and marketing decision-making. This definition requires the simultaneous presence of two components: an AI-mediated technical layer and a stakeholder-inclusive governance structure. Both are necessary, neither is sufficient.

This boundary also clarifies a persistent conflation: four neighboring constructs — AI marketing, digital marketing, co-creation, and stakeholder engagement — are regularly cited interchangeably with AI-enabled participatory marketing, but each occupies a distinct conceptual space. AI marketing (the broader category) is any use of AI in marketing functions regardless of whether the system is influenced by stakeholder inputs — the participatory dimension is absent. Digital marketing is channel specific and AI agnostic. Co-creation research, based on Service-Dominant Logic (Vargo & Lusch, 2004), considers joint value creation without considering AI mediation. The stakeholder engagement based on Freeman et al. (2010) tackles governance and accountability structures without the need for mediation of technology. AI-enabled participatory marketing is the intersection of all four: it requires AI mediation, digital channel infrastructure, co-created value flows and stakeholder governance. These distinctions matter because each adjacent construct predicts different performance outcomes, uses different measurement instruments and has different governance implications. The measurement pluralism currently visible in the field is a direct consequence of this construct conflation.

THE OUTCOMES TURN IN MARKETING TECHNOLOGY RESEARCH

The central question in marketing technology research has shifted over time, from adoption (why do organizations adopt marketing technology?) to implementation (how is it effectively deployed?) to outcomes (what organizational performance does it generate?). Early work was based on the Technology Acceptance Model (Davis, 1989; Venkatesh & Davis, 2000) and focused on the behavior of individual users, a reasonable place to start when technology was new and the problem of adoption

was the one to be resolved. The question then became one of system-level organizational performance as AI-based systems moved from point solutions to enterprise-scale platforms mediating millions of customer interactions. Davenport et al. (2020) describe this as a transition from AI as a tool to AI as operational infrastructure, which is also seen in adjacent technology domains such as AI platform adoption (Nuh et al., 2025), knowledge management applications (Mooradian, 2024) and Trading system (Sukma & Namahoot, 2024a, 2024b, 2024c).

This focus on outcomes has resulted in a heterogeneous literature as organizational performance is theoretically multi-dimensional. The resource-based view (Barney, 1991) explains outcomes through sustainable competitive advantage, Service-Dominant Logic (Vargo & Lusch, 2004) focuses on value co-creation, Dynamic Capabilities Theory (Teece et al., 1997) places organizational agility as an outcome mediator, and Stakeholder Theory (Freeman et al., 2010) considers trust and legitimacy as performance metrics along with the financial return. The Results section documents this measurement pluralism, and the co-existence of these four lenses that generate different outcome constructs and approaches to measurement is the theoretical engine of this pluralism. The practical implication is that results from studies based on RBV framing (measuring sustained differentiation) cannot be directly compared with results from SDL framing (measuring co-creation quality) – making cross-study synthesis structurally difficult without a unifying distributional map as provided by this paper.

An important temporal dimension has constituted this pluralism. Until 2015 marketing technology research was largely normative: should AI tools replace human judgment? After 2015, when AI proved itself to be commercially viable in recommendation engines, programmatic advertising, and customer journey analytics, the research community moved to empirical questions—not whether AI marketing works, but which performance dimensions it improves most reliably. A critical temporal distinction must be drawn within this post-2015 period that the field has only partially addressed. The years 2015–2021 were characterized by one-way, predictive “black-box” AI optimization: algorithmic systems processed stakeholder data to generate marketing outputs, but stakeholders remained passive inputs rather than active co-creators. The post-2022 emergence of generative AI and large language models introduced a qualitatively different model of AI-enabled participation—conversational, bidirectional, and capable of genuine co-creation rather than mere personalization. Tracing participatory marketing back to 2016 without this distinction risks conflating two fundamentally different technological regimes under a single construct. This paper maintains this distinction throughout, treating pre-2022 and post-2022 AI-enabled participation as methodologically and theoretically non-equivalent. After 2015, when AI proved itself commercially viable, the research community moved to empirical questions—not whether AI marketing works, but which performance dimensions it improves most reliably, under what conditions, and at what cost to which stakeholders (Lamberton & Stephen, 2016; Stephen, 2016). Rogers (2003) describes a similar move from innovator-phase speculation to early-majority empirical investigation, and bibliometric analysis can trace this move by tracking the evolution of dominant keyword clusters over time. The acceleration in the volume of publications in 2024 (192.6% year-on-year growth, driven by large language model normalization) is a new innovator-phase surge likely to generate a second wave of measurement pluralism, unless the field’s structural priorities are mapped prior to its arrival.

A second level of theoretical complexity is added by the participatory dimension. These governance structures explicitly incorporate diverse stakeholder groups—consumers, employees, and community members—into system training and marketing decision-making. When AI marketing systems are implemented in such governance structures, the scope of measurable outcomes expands beyond operational efficiency. The operational efficiency models suggest that AI investment creates value mainly for the firm. Participatory co-creation models, by contrast, distribute value across the stakeholder network, but also increase governance complexity: outcomes must be measured not just at the firm level but across the ecosystem of participating actors. This theoretical tension — between firm-centric efficiency models and network-centric co-creation models — has not been resolved by the existing literature. Existing studies tend to draw on one theoretical tradition while neglecting the other:

RBV-grounded studies measure firm-level competitive advantage but ignore stakeholder distribution; S-D Logic studies theorize co-creation richly but rarely operationalize it as a measurable performance outcome. The present bibliometric analysis is motivated precisely by this unresolved tension: by mapping which outcome domains the literature has actually prioritized, we can determine empirically which side of this theoretical divide has captured research attention—and which side remains under-explored. This kind of data-driven diagnosis is what qualitative theoretical reviews of the field have been unable to provide. Participatory co-creation value creation models are more complex in terms of governance architectures but lead to better legitimacy outcomes in distributing value creation across stakeholder networks (Domegan et al., 2016; Payne et al., 2008). Studies of consumer engagement show that participatory digital platforms produce behavioral signals – such as review helpfulness, engagement depth, and content contribution – that AI systems can learn from, creating feedback loops between stakeholder participation and system refinement (Alsharo et al., 2024). The differential characteristic of AI-enabled participatory marketing from AI marketing simpliciter is this feedback loop, the process through which participatory governance structures produce performance benefits.

SIX PERFORMANCE OUTCOME DOMAINS

The determination of performance outcome domains was guided by three theoretical requirements. First, each domain must be traceable to a foundational theoretical tradition, such that the lexicon terms used in the mapping protocol are not idiosyncratic keyword choices, but rather reflective of established scholarly constructs. Second, each domain must be analytically distinct – the boundary between adjacent domains must be theoretically justifiable. Third, the set of domains should be comprehensive in the sense of the current literature. Gaps should be empirical absences, not conceptual omissions. Six analytically distinct performance outcome domains meet these criteria, building on the prior literature (Al-Dmour et al., 2020; Tran et al., 2023) and testing the candidate domain list against the keyword frequency distribution within the Scopus corpus.

Efficiency outcomes refer to reductions in waste, error, and cycle time in marketing operations through AI automation (Lemon & Verhoef, 2016; Rust & Chung, 2006; Wedel & Kannan, 2016). Dynamic Capabilities Theory (Teece et al., 1997) distinguishes operational efficiency as a prerequisite for competitive advantage rather than its equivalent — a distinction that helps interpret efficiency’s 40.3% dominance in the corpus. Stakeholder trust occupies the second-largest outcome domain (38.5%): the construct encompasses consumer, employee, and partner confidence in AI-mediated interactions, centering on algorithmic accountability, the privacy-personalization trade-off, and responsible AI governance (Floridi et al., 2018; Hollebeek et al., 2014). The co-creation domain captures value produced jointly by participatory AI processes — value that neither firm nor stakeholders could generate independently, the central prediction of Service-Dominant Logic (Vargo & Lusch, 2004; Vargo et al., 2008). Where the first three domains ask what AI marketing delivers in the short run, competitive advantage asks whether those gains endure: sustained differentiation that resists competitive imitation (Barney, 1991) requires longitudinal evidence that most corpus studies do not provide. The fourth domain is thus theoretically central but empirically elusive at 30.6% — a gap the research agenda addresses directly in Direction 1. The fifth domain, innovation outcomes — new products, services, and processes enabled by AI participation and open co-creation — draws on S-D Logic’s emphasis on value-in-use and Diffusion of Innovations’ distinction between incremental and discontinuous change (Kannan & Li, 2017; Libai et al., 2020; Piliang et al., 2025). The smallest domain, market reach (8.4%), addresses geographic, demographic, and channel expansion enabled by AI personalization at scale (Rogers, 2003); its underrepresentation is the most consequential structural gap this study documents.

The six domains are theoretically interconnected, and the directionality of those connections has implications for research design. Efficiency and co-creation gains are necessary but not sufficient for competitive advantage: unless AI marketing capabilities are valuable, rare, and inimitable in the sense of Barney (1991), competitive imitation will eliminate the efficiency advantage over time. Service-

Dominant Logic (Vargo et al., 2008) proposes that stakeholder trust mediates the relationship between co-creation quality and market reach — firms with superior trust outcomes access deeper behavioral data, enabling the precision personalization that expands reach. Dynamic Capabilities Theory (Teece et al., 1997) positions organizational agility as a prerequisite for innovation, since discontinuous innovation requires the flexibility to rapidly integrate stakeholder intelligence. Together, these interdependencies produce a testable prediction: single-outcome studies will systematically underestimate the net performance value of AI marketing investment, because they cannot capture the cross-domain spillovers through which efficiency enables advantage, trust enables reach, and agility enables innovation. This prediction provides the theoretical motivation for the integrated research agenda in the Discussion section.

BIBLIOMETRIC ANALYSIS AS METHOD

Bibliometric analysis (Donthu et al., 2021; Zupic & Cater, 2015) is the standard approach for mapping the intellectual structure of emerging management science research domains. Its main advantage over qualitative review methods is quantitative reproducibility: keyword co-occurrence networks, co-citation analyses, and publication trend analyses provide data-driven results that are independent of individual researcher interpretation (van Eck & Waltman, 2010). This is particularly relevant to outcomes research, where the theoretical plurality discussed above increases the risk of confirmation bias in qualitative reviews. Bibliometrics is the right first-stage instrument for RQ1-RQ3; it allows mapping the structural distribution of outcome-related research within a corpus of 467 papers without imposing a pre-determined thematic structure (Paul & Criado, 2020). Its proper complement, which this study does not attempt, is co-citation analysis to map the theoretical foundations of the field at greater resolution (Cobo et al., 2011).

METHODOLOGY

DATA SOURCE AND SEARCH STRATEGY

We downloaded data from Scopus, the world’s largest abstract and citation database of peer-reviewed literature. We chose Scopus because of its extensive coverage of management, marketing, and information systems research and its structured metadata format that is amenable to computational analysis. The following Boolean search string was applied to the title, abstract, and author keyword fields (TITLE-ABS-KEY):

(“artificial intelligence” OR “machine learning” OR “marketing technology” OR “MarTech”) AND (“participatory marketing” OR “co-creation” OR “stakeholder engagement” OR “digital marketing”) AND (“performance” OR “outcomes” OR “efficiency” OR “innovation” OR “competitive advantage”)

One methodological decision warrants transparency. The inclusion of “digital marketing” as an OR alternative within the participatory terms strand introduces breadth that could retrieve studies with no participatory governance dimension. This choice was made deliberately: “participatory marketing” is not yet a standardized Scopus indexing term, and excluding digital marketing studies would risk omitting relevant AI marketing performance research documented under broader terminology. The consequence — acknowledged in the Limitations section — is that the corpus may include studies treating digital marketing broadly without explicit participatory governance structures. The three-stage sequential screening process, including inter-rater reliability verification (Cohen’s $\kappa = 0.84$), was designed to mitigate this risk by requiring substantive treatment of AI marketing or participatory marketing outcomes as a study focus.

The publication window was set from 2015 onwards, to capture the period of the most intensive AI commercialization in marketing contexts; 2015 marks the commercial mainstreaming of programmatic advertising platforms and the beginning of enterprise AI adoption in marketing functions. The search was conducted in April 2026. Initial search yielded 684 records.

INCLUSION CRITERIA AND CORPUS CONSTRUCTION

The initial 684 records were screened by three sequential inclusion criteria. Criterion 1: Documents published in 2015 or later (87 records excluded). Criterion 2: documents had to be peer-reviewed, such as journal articles, conference papers, book chapters or review articles. Editorial letters, errata and non-peer-reviewed commentary were excluded (43 records excluded). Criterion 3: Documents must have substantive treatment of AI marketing or participatory marketing performance outcomes as a primary or secondary focus, operationally defined as at least one of the six performance outcome domains (described in the Theoretical Background section) represented in the title, abstract, or author keywords, or stated as an explicit study objective; papers with only peripheral or incidental mention were excluded (87 records excluded; 554 → 467). The full PRISMA screening path is therefore: 684 → 597 → 554 → 467. The final corpus comprised 467 records, and the PRISMA 2020-compliant flow diagram (Figure 1) presents the complete decision record (Haddaway et al., 2022).

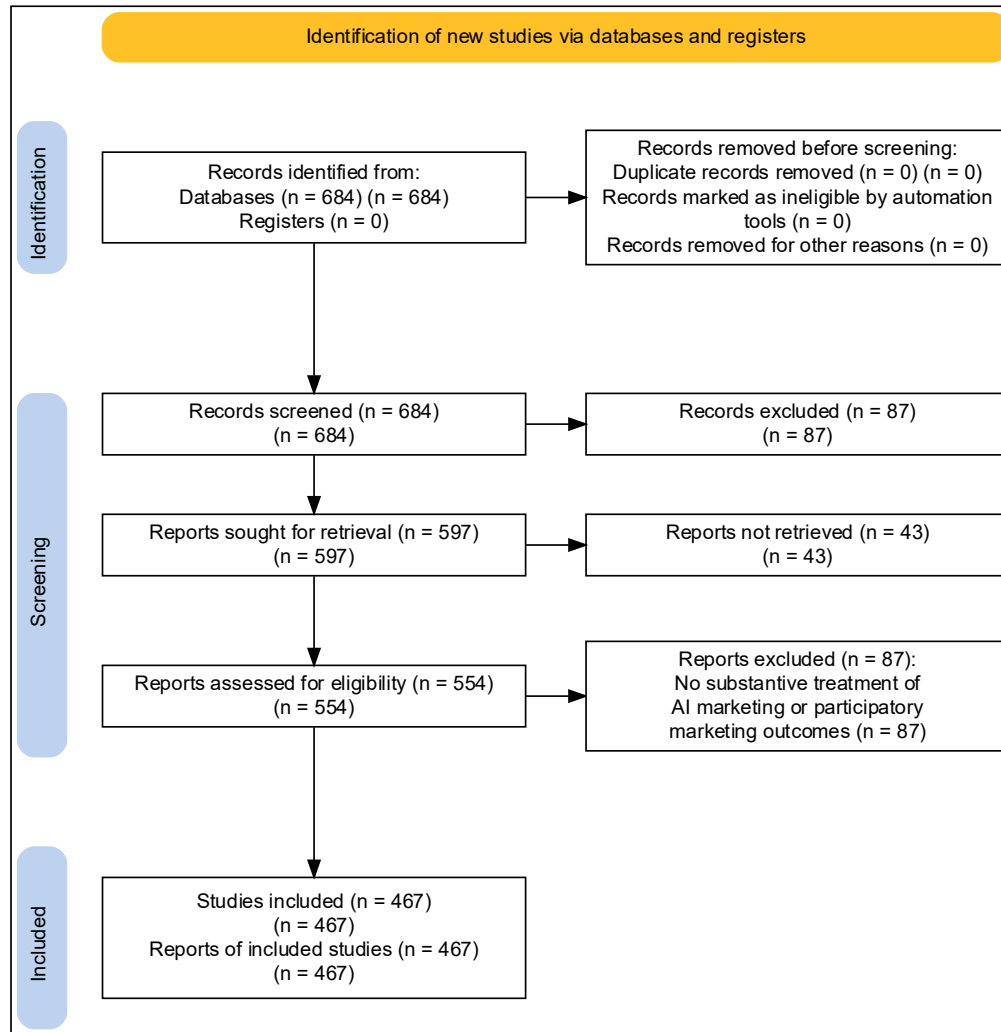


Figure 1. PRISMA 2020-compliant flow diagrams

BIBLIOMETRIC ANALYTICAL TECHNIQUES

Four complementary bibliometric techniques in Python 3.11 (pandas 2.0, collections module) were used to analyze the Scopus metadata exports. Network visualization was performed in VOSviewer 1.6.19 and flow visualization in SankeyMATIC 2024. For publication trend analysis, the growth rate year-over-year and CAGR over the observed period (2015-2024) was analyzed (2025-2026 data are

provisional and hence not included in CAGR calculations). Source and author analysis was performed to determine leading journals, anchor papers and citation concentration. Keyword co-occurrence analysis identified the structural relationships of 892 unique author keywords, with cluster identification by the modularity-based algorithm of VOSviewer. Cluster labels were assigned by the research team based on the three highest-frequency keywords within each VOSviewer-generated cluster, cross-validated against the domain definitions in the Theoretical Background section.

Performance outcome mapping was developed by creating lexicons specific to the 8-14 outcomes per domain. These lexicons integrated the theoretical definitions from the principal framework of each domain (Barney, 1991; Freeman et al., 2010; Rogers, 2003; Teece et al., 1997; Vargo & Lusch, 2004) with the most common author keywords in the corpus. The complete lexicons are given in Table 5 of this paper. We counted a paper as related to a given outcome domain when at least one lexicon term was present in the title, abstract, or author keywords. Matching was case-insensitive and applied to whole-word tokens; stemming was not applied to preserve domain-term specificity. As a validation step, a 10% random sub-sample ($n = 47$ papers) was also independently coded by a second researcher; Cohen's kappa = 0.84 indicates strong inter-rater agreement. Disagreements were worked out by discussion to a consensus. Cross-domain overlap was permitted as the research questions focus on the distribution of outcome coverage, not mutual exclusivity.

To examine temporal evolution, the corpus was divided into two sub-periods based on the inflection noted in Table 1: 2015–2020 (pre-acceleration phase, $n = 123$) and 2021–2026 (acceleration phase, $n = 344$). The empirical rationale for this division is the 72.2% growth observed in 2020. The theoretical basis is outlined in Davenport et al.'s (2020) discussion of the post-2019 diffusion of AI into enterprise marketing, which signifies a structural shift from mere adoption to a focus on outcomes research. Further details can be found in the data availability sub-section at the end of this paper (**S1–S6**).

RESULTS

PUBLICATION TRENDS: A FIELD AT INFLECTION

The 467-paper corpus has a three-phase growth pattern: (1) an initial growth spurt (2015-2016, CAGR +125.0%), (2) a methodological stabilization phase (2017–2023, CAGR approximately 8.0%), (3) a fresh acceleration from 2024 with 192.6% year-on-year growth (Table 1). The number of annual publications increased from 12 in 2015 to 79 in 2024, with an overall CAGR of 23.3% over the nine fully observed years. This three-phase trajectory parallels the Rogers (2003) diffusion of innovations model, with the initial surge representing the innovator-phase enthusiasm, the consolidation phase representing methodological discipline as early-majority researchers entered the field, and the 2024 acceleration representing a new innovator-phase surge triggered by the commercial normalization of large language model deployment following the release of GPT-4 in March 2023.

Two events of secondary growth are to be interpreted. The 2016 surge (+125.0%) coincided with the commercial mainstreaming of programmatic advertising — the first AI-driven marketing technology to reach scale deployment. The 2020 acceleration (+72.2%) was accompanied by the COVID-19 imposed digitalization of marketing functions across all industries, which exposed organizations to AI marketing tools, previously the preserve of digital native firms. Both events appear in the keyword co-occurrence data as inflection points where new terminology entered the corpus. The partial year data for 2025 (roughly 151 papers through roughly 10 months of export) indicates an acceleration that, if sustained, would reach roughly 180-200 papers by December 2025 – a provisional projection that should be treated with caution and presented in Figure 2.

Table 1. Publication trends in AI-enabled participatory marketing research

Year	Annual N	Cumul. N	YoY Growth	Phase	Contextual Note
2015	12	12	—	Inception	Field emergence; AI as emerging marketing concept
2016	27	39	+125.0%	Early growth	Commercial programmatic ad platforms mainstream
2017	17	56	−37.0%	Methodological consolidation	Post-surge stabilization; methodological papers dominant
2018	18	74	+5.9%	Consolidation	AI ethics discourse begins; GDPR enacted (May 2018)
2019	18	92	0.0%	Pre-acceleration plateau	Stable output; AI adoption mainstream in enterprise
2020	31	123	+72.2%	COVID-19 AI surge	Accelerated digital-first pivot; AI marketing tools scale
2021	32	155	+3.2%	Post-surge consolidation	Methodological consolidation following 2020 growth spike
2022	28	183	−12.5%	Consolidation	Privacy regulation discourse intensifies (GDPR enforcement)
2023	27	210	−3.6%	Pre-LLM plateau	Final consolidation before large language model normalization
2024	79	289	+192.6%	LLM acceleration	GPT-4 and enterprise LLM deployment in commercial marketing
2025	~151	~440	~+91.1%	Rapid growth	Partial-year projection; not included in CAGR calculation
2026 (partial)	~27	~467	—	In progress	Partial export; provisional only
TOTAL (2015–2024)	289	—	CAGR: 23.3%	9-year observed	2025–2026 provisional only; excluded from CAGR

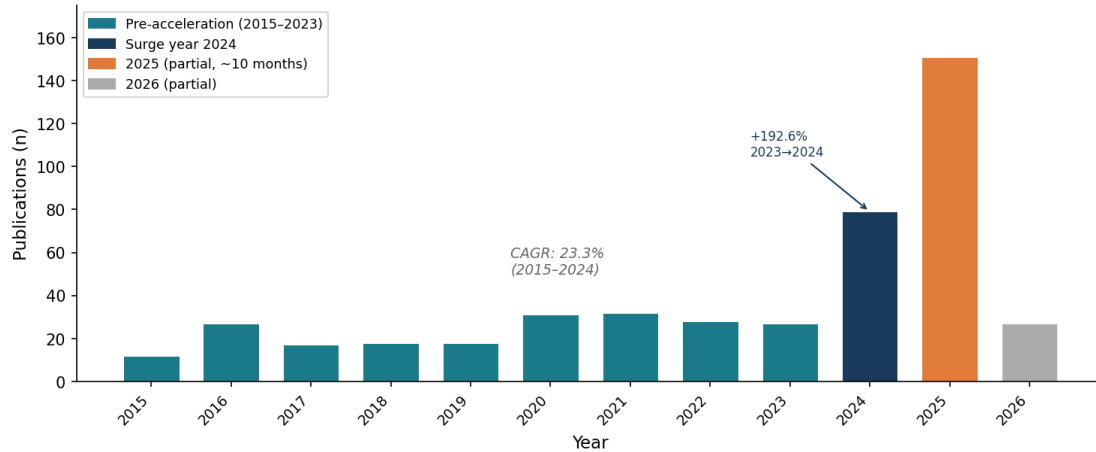


Figure 2. Annual publication volume in AI-enabled participatory marketing research

LEADING SOURCES AND INTELLECTUAL ANCHORS

The 467 papers were published in 151 source outlets (Table 2), which is a concentration ratio consistent with a pluralistic but maturing field of marketing science, information systems, sustainability research, and organizational behavior. The top 11 source journals listed in Table 2 collectively comprise approximately 13.7% of the total output, and the remaining 86.3% is distributed across 140 further outlets, confirming that the field has not yet consolidated around a small number of dominant venues. This dispersion has implications for the accumulation of knowledge: high venue diversity is typically associated with low cross-citation density, which slows down the development of methodological consensus (Zupic & Cater, 2015).

The conceptual distinction between AI as tool versus AI as infrastructure, which maps directly to the efficiency versus competitive advantage split in the bibliometric clusters, is established by Davenport et al. (2020). The theoretical case for continuous stakeholder feedback mechanisms is based on Lemon and Verhoef (2016). Sivarajah et al. (2017) identify the data analytics challenges that limit the measurement of efficiency outcomes. Dwivedi et al. (2021) provide the most widely referenced multi-disciplinary synthesis of AI challenges and opportunities relevant to the 2021–2024 growth phase.

Table 2. Top source journals in the AI-enabled participatory marketing corpus

Source Journal / Outlet	Papers	% Total	Avg. Cit.	Primary Research Domain
Journal of Business Research	10	2.1%	84.3	Marketing strategy and technology
Smart Innovation, Systems and Technologies	10	2.1%	12.1	Technology and innovation systems
Sustainability	7	1.5%	31.7	Sustainable marketing and AI ethics
IJKM	6	1.3%	21.8	AI adoption, knowledge management, digital engagement
Journal of the Academy of Marketing Science	5	1.1%	198.4	Marketing science and AI strategy
Technological Forecasting and Social Change	5	1.1%	156.2	Technology forecasting

Source Journal / Outlet	Papers	% Total	Avg. Cit.	Primary Research Domain
Journal of Retailing	5	1.1%	143.8	Retail and consumer behavior
Journal of Marketing	4	0.9%	201.5	Core marketing science
Industrial Marketing Management	4	0.9%	88.6	B2B marketing and stakeholder relations
Computers in Human Behavior	4	0.9%	67.3	Human-computer interaction
Information and Management	4	0.9%	79.4	IS and organizational performance
All other outlets (140 journals)	403	86.3%	—	—

THEMATIC CLUSTER ANALYSIS

The performance outcome mapping protocol together with the co-occurrence analysis of 892 unique author keywords produced five coherent research clusters (Table 3). The two most dominant intellectual territories are Cluster 3 (Stakeholder and Participatory Engagement, 58.9%) and Cluster 5 (Performance and Competitive Outcomes, 60.0%), each of which includes more than half of the corpus papers. The significant overlap between these two clusters—papers can belong to both simultaneously, reflecting co-occurring research themes—embodies the core theoretical tension of the field: the empirically underdetermined relationship between participatory governance processes and the performance outcomes they are designed to produce which presented in Figure 3.

Cluster 1 (AI and Data Infrastructure, 37.3%) is concerned with technical enablers — machine learning architecture, big data pipelines, and predictive analytics systems. The main keywords are artificial intelligence (69), digital marketing (60), big data (22), and predictive analytics (16). Cluster 2 (Digital Marketing Strategy, 33.0%) relates to strategic implementation: channel integration, content marketing and marketing automation. Cluster 3 (Stakeholder and Participatory Engagement 58.9%) delineates the governance and relational mechanisms through which AI systems incorporate diverse stakeholder inputs — consumer preferences, employee feedback, and community data — into marketing decision-making, grounded in Stakeholder Theory (Freeman et al., 2010) and Service-Dominant Logic (Vargo & Lusch, 2004). Cluster 4 (Organizational Dynamics and Leadership, 30.0%) is the smallest cluster and its keyword profile is characterized by the emotional intelligence (27 occurrences), transformational leadership (11) and team communication (11), confirming that organizational enablers of AI marketing performance are systematically underrepresented in relation to technical and strategic dimensions – a pattern with direct implications for Gaps 1 and 3 identified in the Discussion section.

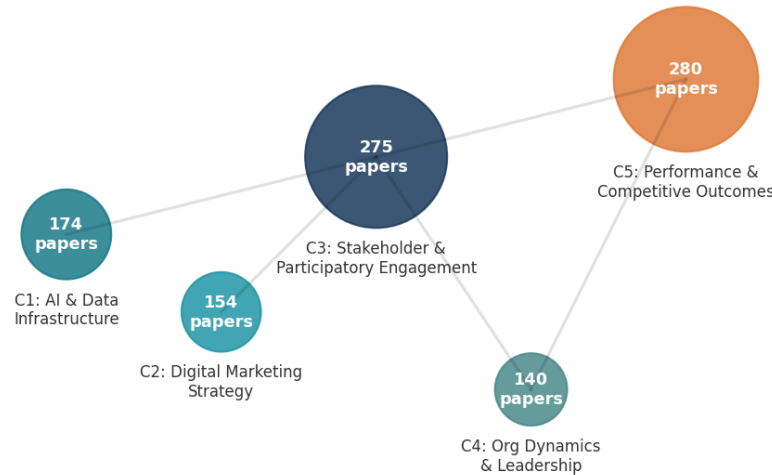


Figure 3. Thematic cluster map of the AI-enabled participatory marketing literature

Temporal disaggregation reveals a pattern of structural importance. Cluster 5 (Performance and Competitive Outcomes) grew faster in the acceleration phase (2021–2026: 61.9%) than in the pre-acceleration phase (2015–2020: 54.5%), while Cluster 4 (Organizational Dynamics and Leadership) decreased from 32.2% to 29.2%. The increase in publications has consolidated the already dominant streams of research, rather than diversifying into the underrepresented dimensions of organizational enablement. This structural deepening will worsen, not solve, the representational imbalances documented in this study as the field’s publication volume accelerates toward the 2027 horizon.

Table 3. Thematic cluster analysis of the AI-enabled participatory marketing corpus

#	Cluster Name	N Total	% Total	% 2015-2020 (n = 123)	% 2021-2026 (n = 344)
1	AI and Data Infrastructure	174	37.3%	31.4%	39.3%
2	Digital Marketing Strategy	154	33.0%	28.0%	34.7%
3	Stakeholder and Participatory Engagement	275	58.9%	55.1%	60.4%
4	Organizational Dynamics and Leadership	140	30.0%	32.2%	29.2%
5	Performance and Competitive Outcomes	280	60.0%	54.5%	61.9%

Note. Papers may be assigned to more than one cluster. Percentages represent the proportion of the 467-paper corpus assigned to each cluster and do not sum to 100%.

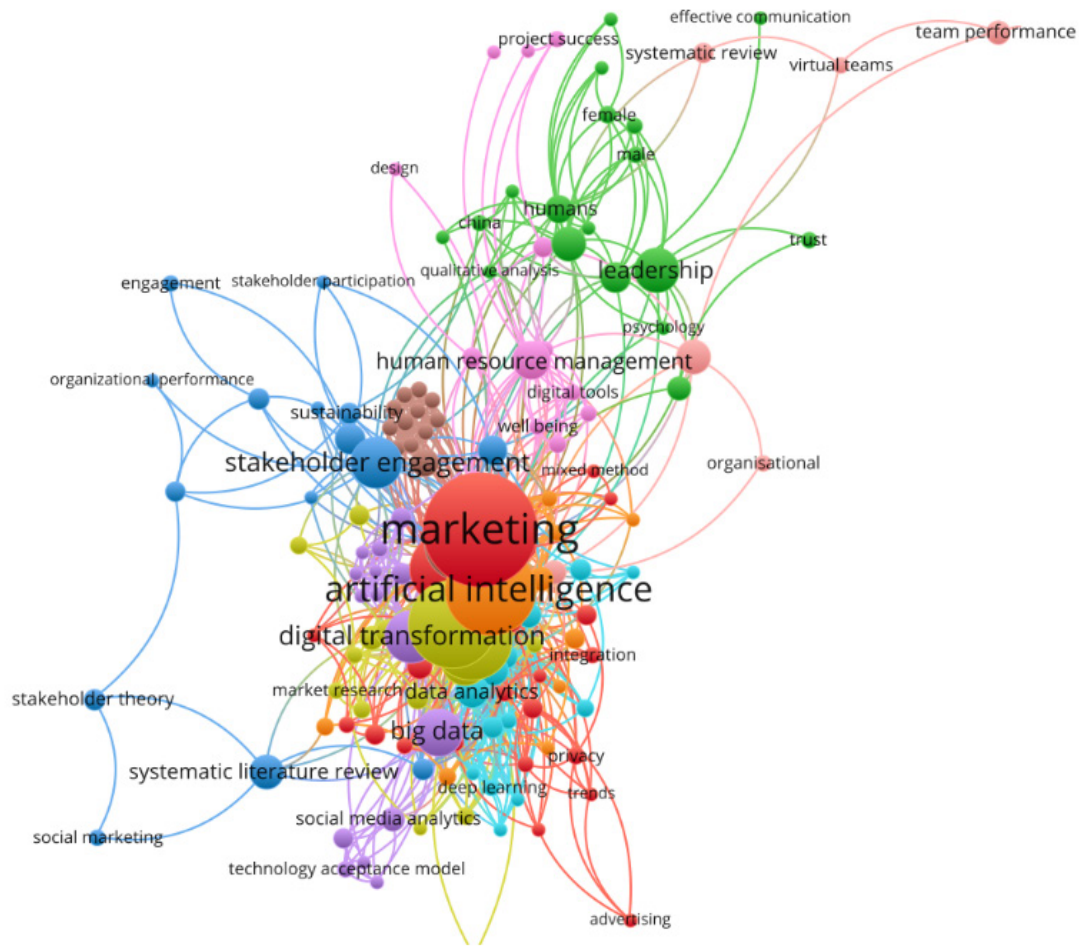


Figure 4. Hub-filtered keyword co-occurrence network

Figure 4 presents a hub-filtered view retaining only the thirty nodes with highest degree centrality, providing a cleaner representation of the field's structural core. 'Marketing' (orange, center-left) and 'marketing strategy' (red, center) emerge as the two most connected hubs, collectively linking consumer, strategic, and technological sub-communities. 'Stakeholder engagement' (orange, lower-center) maintains strong ties to both marketing and digital transformation clusters, consistent with the participatory co-creation logic embedded in the Transformative Engagement and Participation Model (TEPM). Critically, the 'leadership' node (green, isolated right) displays minimal connectivity to any other hub, reinforcing the argument advanced in results section that leadership and governance constructs have not been systematically integrated into the quantitative mainstream. This structural gap represents a theoretically significant research opportunity: future empirical studies linking leadership styles to co-creation outcomes could substantially strengthen the field's governance foundations and increase its policy relevance.

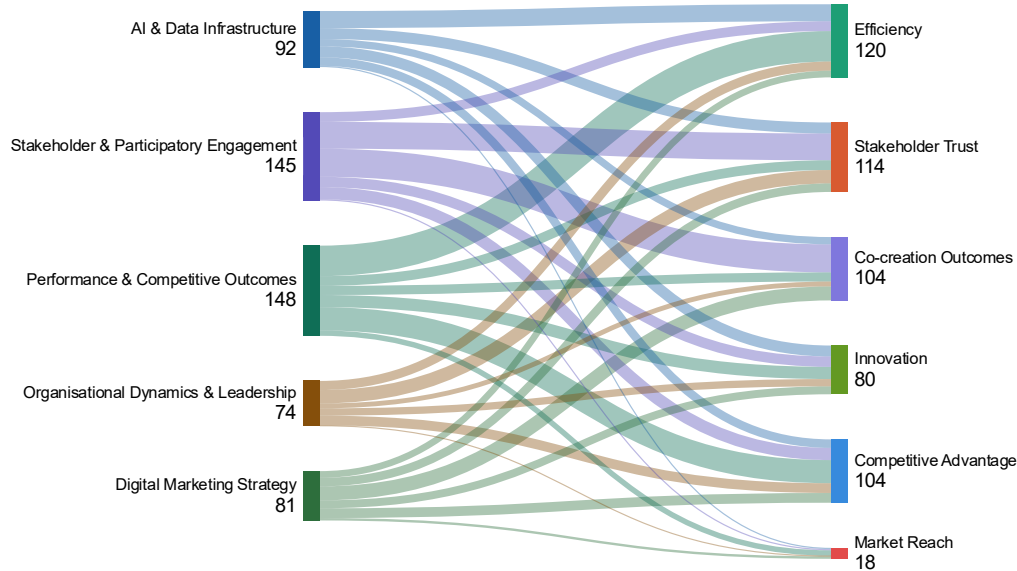


Figure 5. Sankey flow diagram mapping cross-classification between thematic clusters

Figure 5 presents a Sankey flow diagram mapping the structural relationship between the five thematic clusters identified in the Results section and the six performance outcome domains quantified. Each node on the left represents a thematic cluster, and each node on the right represents a performance outcome domain; flow width is proportional to the number of paper-outcome keyword matches, producing a total of 540 cross-classified connections across the 467-document corpus. The diagram reveals three structural patterns that are not immediately visible in the tabular cluster analysis. First, Co-creation is the dominant receiving node, drawing substantial flows from all five clusters—confirming that participatory value generation is the field’s most broadly shared outcome construct regardless of theoretical starting point. Second, the Stakeholder Engagement cluster channels the largest single flow (64 matches) directly into Co-creation while contributing negligibly to Market Reach, illustrating the asymmetry identified in research results between external engagement research and market expansion outcomes. Third, and most critically, the Market Reach node receives only five flows totaling five matches—a near-invisible sliver relative to every other outcome domain—providing a direct visual representation of the critical gap documented in Gaps. Taken together, Figure 5 transforms the distributional statistics reported in Table 4 into a relational map that shows not only how much research addresses each outcome, but which intellectual communities are generating it, and which pathways remain structurally absent from the field’s current trajectory.

PERFORMANCE OUTCOME MAPPING: DISTRIBUTION AND GAPS

The performance outcome mapping reveals a highly uneven distribution across the six domains, directly addressing RQ2. The most studied outcome is efficiency (40.3%, $n = 188$), which is consistent with a diffusion pattern in the early stage for operational technologies: organizations typically adopt AI marketing tools for the purpose of cost reduction and throughput gains before higher-order strategic outcomes can be measured. The second most studied domain is stakeholder trust (38.5%, $n = 180$), which aligns with the expansion of privacy regulation and algorithmic accountability discourse following the enforcement of the European Union’s General Data Protection Regulation in 2018 and the California Consumer Privacy Act in 2020. Co-creation outcomes (36.2 %, $n = 169$) and competitive advantage (30.6 %, $n = 143$) occupy a middle tier. Innovation outcomes (28.9%, $n=135$) are underrepresented in comparison to their theoretical prominence within the SDL and Dynamic Capabilities perspectives.

Table 4. Performance outcome domain distribution across the bibliometric corpus

Outcome Domain	N Papers	% Corpus	Theoretical Grounding	Key Constructs and Keywords
Efficiency	188	40.3%	Dynamic Capabilities Theory (Teece et al., 1997)	Cost reduction, throughput automation, ROI, process optimization, operational efficiency
Stakeholder Trust	180	38.5%	Stakeholder Theory (Freeman et al., 2010)	Consumer trust, algorithmic transparency, privacy, accountability, responsible AI
Co-creation Outcomes	169	36.2%	Service-Dominant Logic (Vargo & Lusch, 2004)	Value co-creation, collaborative design, user-generated content, open innovation, crowdsourcing
Competitive Advantage	143	30.6%	Resource-Based View (Barney, 1991)	Sustained differentiation, market leadership, VRIN capabilities, strategic advantage
Innovation	135	28.9%	S-D Logic; Diffusion of Innovations (Rogers, 2003)	New product development, creativity, disruptive innovation, R&D output, ideation
Market Reach	39	8.4%	Diffusion of Innovations (Rogers, 2003)	Geographic expansion, customer acquisition, audience growth, market penetration, cross-border

Note. Papers may be assigned to more than one outcome domain. Percentages represent the proportion of the 467-paper corpus classified within each domain and do not sum to 100%.

The most significant finding is the marked underrepresentation of market reach outcomes (8.4%, $n = 39$), despite market expansion being one of the key business rationales for AI marketing investment. This gap is explained methodologically, which adds to its theoretical significance: estimating market reach requires longitudinal data on the acquisition of customers across geographic or demographic divides, data that the cross-sectional survey designs that dominate the corpus are unable to supply. The practical implication is that the construct that is most relevant to the business case for AI marketing investment (does AI marketing grow the market?) is the construct with the least evidence. This is the empirical gap that motivates the most pressing research priority in the Discussion section. The lexicons used for classification are provided in Table 5 to enable replication.

Table 5. Performance outcome classification keyword lexicons

Outcome Domain	Classification Keywords (matched against Title + Abstract + Author Keywords)
Efficiency	efficiency; operational efficiency; marketing performance; automation; productivity; ROI; cost reduction; workflow; lean; process optimization
Stakeholder Trust	trust; stakeholder trust; consumer trust; brand trust; loyalty; credibility; transparency; privacy; ethics; ethical AI; responsible AI; data privacy
Co-creation Outcomes	co-creation; value co-creation; collaborative; collaboration; participatory; stakeholder engagement; community; user-generated; crowdsourcing; open innovation

Outcome Domain	Classification Keywords (matched against Title + Abstract + Author Keywords)
Competitive Advantage	competitive advantage; sustainability; sustainable; differentiation; market leadership; strategic advantage; first-mover; value creation; competitive differentiation
Innovation	innovation; innovativeness; new product development; creativity; R&D; novelty; product innovation; disruptive; breakthrough; ideation
Market Reach	market reach; market expansion; customer acquisition; market share; geographic expansion; new markets; penetration; audience growth; cross-border; internationalization

SIX-DIRECTION RESEARCH AGENDA

The bibliometric evidence supports six research directions (Table 6), each grounded in a specific structural gap. Figure 6 provides a visual summary of the six research directions detailed in Table 6, constituting a methodological rebalancing program for the field rather than a list of incremental extensions of existing work.

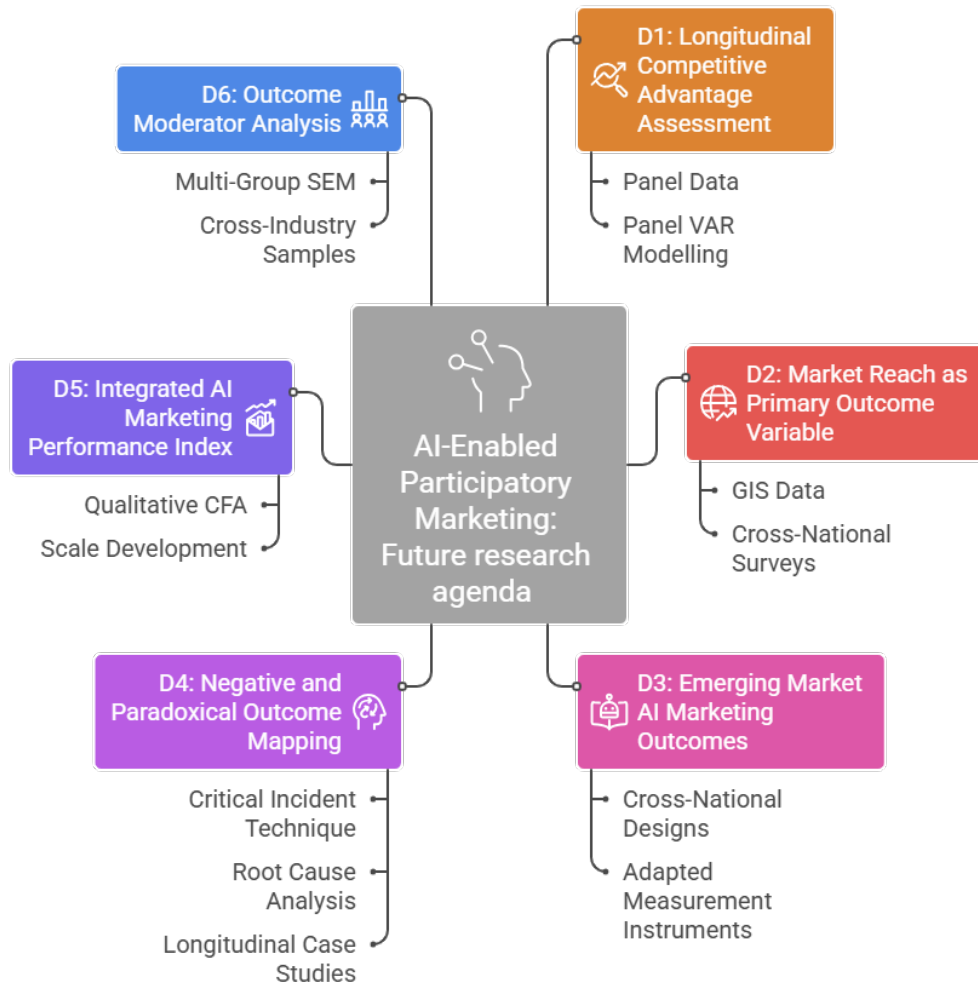


Figure 6. Six-direction future research agenda

Table 6. Six-direction future research agenda derived from bibliometric gap analysis

Dir.	Research Direction	Gap Addressed	Recommended Method	Key References
D1	Longitudinal competitive advantage assessment	Cross-sectional design dominance; competitive advantage empirically elusive	Panel data over 3-5 years; Panel VAR modelling	Barney, 1991; Morgan, 2012; Vorhies & Morgan, 2005
D2	Market reach as primary outcome variable	Critical underrepresentation (8.4% of corpus)	Mixed methods: GIS data + cross-national organizational surveys	Rogers, 2003; León-Castro et al., 2021; Tran et al., 2023
D3	Emerging market AI marketing outcomes	Geographic concentration in Western and East Asian contexts	Cross-national comparative designs; adapted measurement instruments	Al-Azawei, 2018; Badouch & Boutaounte, in press; Durman & Nadlifatin, 2024
D4	Negative and paradoxical outcome mapping	Positivity bias; failure modes systematically absent	Critical incident technique; root cause analysis; longitudinal case studies	Floridi et al., 2018; Paschen et al., 2020
D5	Integrated AI Marketing Performance Index (AMPI)	Fragmented single-outcome studies; no cross-domain measurement instrument	Sequential mixed methods: qualitative CFA + large-scale scale development	Mooradian, 2024; Donthu et al., 2021; Zupic & Carter, 2015
D6	Outcome moderator analysis (industry, firm size, AI maturity)	Organizational context neglected; Cluster 4 proportionally declining	Multi-group SEM with large cross-industry samples (N > 500)	Piliang et al., 2025; Durman & Nadlifatin, 2024; Teece et al., 1997

Sustained competitive advantage — by definition a temporal claim — can only be empirically validated through longitudinal designs. Direction 1 therefore calls for panel data studies tracking firm-level AI marketing investments and competitive outcomes over three to five years, providing the first direct tests of Barney's (1991) sustained competitive advantage predictions in AI marketing contexts. Panel VAR (vector autoregression) models are particularly suited to this purpose: they enable dynamic modeling of the feedback between efficiency gains, competitor adoption rates, and sustained differentiation, answering the fundamental question of whether early AI marketing adoption produces durable advantage or merely temporary operational superiority.

Market reach has been treated as a peripheral correlate of efficiency rather than as an independent outcome worthy of primary theoretical attention. Elevating it to a primary dependent variable — the core argument of Direction 2 — requires research designs that observe reach dynamics over time and across contexts. Mixed methods combining GIS data with organizational survey instruments would allow simultaneous measurement of actual reach expansion and the AI governance structures that produce it, while controlling for confounds such as pricing strategy, product innovation, and competitive entry. Studies of this kind would give the field its first empirical answer to the question of how much AI-enabled personalization translates into genuinely new market coverage rather than simply intensifying reach within existing segments.

The geographic concentration of the corpus in Western Europe, North America, and East Asia is not merely a representational problem — it is a validity problem, because the organizational contexts most in need of AI marketing guidance are the ones least represented. Direction 3 argues for studies designed around emerging market contexts from inception, rather than replications of Western frameworks with modified samples. In settings where market formalization, first-purchase customer acquisition, and cross-sector stakeholder network development are the primary outcome dimensions, transplanted frameworks from advanced markets systematically misfit local realities (Durman & Nadlifatin, 2024; Kala et al., 2024). Technology adoption research has consistently demonstrated that contextually adapted frameworks produce significantly different outcomes compared to directly transplanted models, suggesting that emerging market AI marketing research requires original theoretical development, not only adapted measurement.

One of the clearest indicators of a maturing research field is the willingness to document failure as rigorously as success. Direction 4 proposes a systematic research program on adverse outcomes and failure modes: when and why does AI marketing produce privacy breaches, trust erosion, stakeholder exclusion, and algorithmic bias? Critical incident technique adapted to organizational settings, combined with root cause analysis and longitudinal tracking of trust recovery trajectories, would provide the failure-mode documentation the field currently lacks. Understanding these failures is not an esoteric methodological interest — it is the empirical precondition for credible responsible AI governance recommendations in high-stakes domains where AI marketing systems are rapidly scaling.

Fragmented single-outcome studies cannot support the cross-firm or cross-industry performance comparisons that managers and policymakers require for investment decisions. Direction 5 proposes the development of an integrated AI Marketing Performance Index (AMPI) that measures all six outcome domains simultaneously, making performance comparable across firms, industries, and contexts. As Mooradian (2024) argues, AI-intensive knowledge domains require structured performance frameworks to differentiate value creation from value extraction across stakeholder networks. A sequential mixed-methods design — qualitative construct validation with expert panels, followed by large-scale confirmatory factor analysis across multiple industries — would provide the measurement rigor an index of this kind requires (Donthu et al., 2021; Zupic & Cater, 2015).

The boundary conditions that moderate AI marketing effectiveness remain poorly understood: does the relationship between AI investment and efficiency outcomes vary by industry sector, firm size, or AI maturity stage? Cluster 4 papers most frequently theorize about these moderators but least frequently measure them. Direction 6 calls for multi-group SEM analyses with large cross-industry samples ($N > 500$) to simultaneously identify which boundary conditions are universal — applying across all six outcome domains — and which are domain-specific, applying only to trust or only to competitive advantage. Beyond identifying specific moderators, this direction addresses the deeper generalizability question: under what organizational conditions does current knowledge about AI marketing outcome relationships hold, and where does it break down? Answering that question is the precondition for responsible scale-up of AI marketing investment recommendations (Durman & Nadlifatin, 2024; Piliang et al., 2025).

DISCUSSION

THREE STRUCTURAL GAPS

Gap 1: Dominance of cross-sectional designs

Competitive advantage is by definition a temporal proposition: an advantage is ‘sustained’ only if it endures through competitive responses (Barney, 1991). Cross-sectional designs dominate the corpus, such as surveys, case studies at a single point in time, and archival analyses in a single period. These can document short-term efficiency gains but cannot determine whether they endure as competitors develop equivalent AI capabilities (Morgan, 2012; Vorhies & Morgan, 2005). The 30.6% competitive advantage coverage in Table 4 substantially overstates the longitudinal evidence available: a keyword

match on “competitive advantage” does not constitute an empirical test of sustained advantage. Throughout this analysis, publication frequency is treated as a measure of research attention rather than theoretical importance or empirical validity; interpretive claims about the distribution are grounded in the theoretical frameworks of the Theoretical Background section, not in frequency counts alone. Close reading of the corpus papers in this cluster reveals that most papers theorize about advantage potential rather than demonstrating sustained differentiation. This is not a minor methodological limitation, but a structural threat to the validity of the main theoretical claims of the field. Dynamic capabilities cannot be shown from a single cross-sectional observation, but they have to be observed over competitive cycles (Teece et al., 1997). In particular, technology forecasting requires temporal data on the unfolding of performance effects as systems mature, competitors respond, and stakeholder relationships deepen (Bengisu & Nekhili, 2006; Pantano & Pizzi, 2020).

Gap 2: Geographic and cultural underrepresentation

The data on institutional affiliations show that the corpus is heavily biased toward Western Europe, North America and East Asia. Emerging market contexts, i.e., Southeast Asia, Sub-Saharan Africa, and Latin America, are underrepresented despite a growing share of AI marketing investment crucially, these represent the settings where market reach expansion is most theoretically and practically relevant (León-Castro et al., 2021; Tran et al., 2023). Less than 5% of the corpus papers are set in Southeast Asian contexts. This concentration is not simply a representational concern; it creates problems of theoretical boundary condition. Efficiency and trust outcome findings from Western organizational contexts are being imported into emerging market strategy recommendations that may not be held when institutional environments, regulatory frameworks and stakeholder expectations are structurally different (Al-Azawei, 2018; Badouch & Boutaounte, in press; Shetty et al., 2025). The mismatch between the geographical distribution of AI marketing research and the geographical distribution of AI marketing deployment creates a knowledge transfer problem of increasing practical relevance. These two gaps — methodological and geographic — are structurally connected: both reflect a field that has documented AI marketing performance primarily in contexts where adoption is advanced and cross-sectional measurement is organizationally feasible, creating a compound bias toward best-case outcomes in best-practice settings.

Gap 3: Positivity bias and neglect of adverse outcomes

The corpus is much more likely to document the successes of AI marketing than the failures or damage that occur when it is poorly implemented. This positivity bias is typical of early-stage technology research (Rogers, 2003) but becomes theoretically and practically consequential as AI marketing systems scale into high-stakes domains — political advertising, financial services, healthcare communications — where failure modes carry asymmetric risks. A small minority of the corpus comprises papers reporting AI marketing failures, unintended harms, or performance-degrading implementations (Floridi et al., 2018; Paschen et al., 2020). The privacy-personalization trade-off, where the depth of data needed for personalization effectiveness leads to increased privacy risk, is present in less than 10% of corpus papers despite its theoretical centrality to the stakeholder trust domain. Relatedly, there is a neglect of the second-order organizational consequences of AI adoption in marketing: as AI systems take over from targeting, segmentation and content generation, organizations need to reorganize marketing functions in ways that affect decision authority, team composition and the scope of human judgment in brand management (Kietzmann et al., 2018; Libai et al., 2020). The current corpus largely omits these second-order organizational consequences.

THEORETICAL IMPLICATIONS

The bibliometric distribution addresses RQ3 and has three theoretical implications on the conceptual architecture of the field.

First, the preponderance of efficiency (40.3%) and trust (38.5%) as outcome constructs, combined with the near non-existence of market reach (8.4%), indicates that the field has implicitly theorized AI marketing as an operational optimization technology rather than a market expansion technology.

This implicit choice has consequences: AI marketing, theories of operational optimization predict, makes organizations better at what they already do, improving efficiency within existing markets. Diffusion of Innovations (Rogers, 2003) and network effects models of market expansion theory suggest that AI marketing reduces the unit cost of personalized communication, allowing organizations to tap into previously unreachable stakeholders and markets. These are not minor theoretical variations but lead to fundamentally different empirical predictions and governance recommendations. By consistently measuring efficiency and trust while neglecting market reach, the literature has described the internal mechanics of AI-enabled participatory marketing while leaving untested Service-Dominant Logic's central prediction: that co-creation quality mediates the relationship between AI governance structures and market expansion (Vargo & Lusch, 2004; Vargo et al., 2008). Resolving this gap is not just a measurement problem — it requires theorizing AI-enabled participatory marketing as a market-building technology, not only an operational efficiency tool.

Second, the relative size of Cluster 3 (Stakeholder and Participatory Engagement, 58.9%) versus Cluster 4 (Organizational Dynamics and Leadership, 30.0%) reveals a structural asymmetry in how the field theorizes participatory processes. The field has studied what participatory AI marketing produces externally — engagement, co-creation outputs, trust — at nearly twice the rate it has studied the internal organizational conditions that determine whether genuine participation is even possible. This asymmetry matters because participation quality is not solely a function of the technical AI system; it is jointly determined by leadership commitment to multi-stakeholder governance, team communication structures that channel stakeholder feedback into system refinement, and organizational culture that tolerates the uncertainty inherent in co-created outcomes. When the literature treats these internal enablers as peripheral rather than constitutive, it implicitly accepts a model of participatory marketing in which the AI system does the participatory work while organizational structures remain unchanged. That model is theoretically inconsistent with Stakeholder Theory (Freeman et al., 2010), which situates stakeholder engagement as a governance responsibility, not a technical feature. The most frequently referenced empirical research consistently highlights internal factors — leadership capabilities, team communication structures, organizational culture — as the primary drivers of whether AI marketing systems actually result in the co-creation and trust outcomes that external engagement is theoretically expected to produce (Brodie et al., 2011; Prahalad & Ramaswamy, 2004). The feedback loops through which stakeholder intelligence improves AI system performance do not work as the theory predicts in the absence of sufficient organizational infrastructure for participation.

Third, the finding of temporal disaggregation — that the acceleration phase of 2021-2026 did not diversify but rather deepened the representational imbalances of the corpus — has a prospective theoretical implication. If the current wave of LLM-driven research continues to favor efficiency and directs research toward trust because these are methodologically tractable outcomes in cross-sectional designs, the field risks entering a period of systematic theoretical narrowing precisely when its empirical base is expanding most rapidly. The six-direction agenda seeks to break this narrowing by creating methodological incentives for studying the outcomes, market reach, longitudinal competitive advantage, adverse outcomes, that current design preferences systematically suppress.

CONCLUSION

This study documents a structural imbalance, not a random one — and the distinction matters fundamentally for how the field designs its next research cycle. The overrepresentation of efficiency and trust outcomes is not a failure of individual researchers; it is the predictable consequence of measurement convenience in a young field. Single cross-sectional studies can operationalize efficiency in a single survey wave. Competitive advantage, market reach, and innovation cannot be measured this way — and the fact that they have not been systematically measured is itself a finding with consequences for theory and practice. The field has not simply ignored these outcomes; it has constructed a methodological infrastructure that makes measuring them difficult. The research agenda proposed

here is therefore not a list of gaps but a set of design recommendations for breaking that infrastructure and redirecting empirical attention toward the outcome domains that most determine whether AI marketing investment creates lasting value.

The bibliometric corpus of 467 Scopus-indexed records (2015-2026, CAGR = 23.3%) shows five thematic clusters and six performance outcome domains with a systematic unevenness. The most acute imbalance – market reach at 8.4% versus efficiency at 40.3% – has a precise remedial program: Direction 2 of the research agenda considers geographic, demographic, and channel expansion as key dependent variables in longitudinal, GIS-enabled, mixed-methods designs. Directions 1, 3, 4, 5, and 6 address complementary design, geographic, positivity, measurement, and moderator gaps that together limit the field’s theoretical validity and practical applicability. As the annual output of papers in the field reaches and might even surpass 200 in 2025-2026, the need for this type of structural self-understanding will increase, not decrease. The research agenda proposed here is meant to provide directional guidance before the next surge adds to the already existing imbalances.

The stakes extend beyond the field itself. As AI marketing systems move from early-adopter experiments to core commercial and governmental infrastructure, the capacity of informing science and knowledge management research to supply structured, multi-domain performance evidence becomes a societal asset. A literature that measures only what is easy to measure — efficiency and trust in cross-sectional surveys — will inform AI governance frameworks that are systematically blind to market reach, innovation, and competitive dynamics. The six-direction agenda proposed here is, at its core, an argument for building the kind of knowledge infrastructure that AI-era marketing decisions actually require. This study has three limitations. Bibliometric analysis can describe publication patterns, but cannot assess the causal validity of individual studies. A large number of publications in a domain reflects research attention, not empirical resolution. The keyword-matching protocol may not identify papers that use non-standard terminology for well-established constructs, and the inclusion of “digital marketing” in the Boolean string may have introduced some breadth into the corpus that future replication studies with a stricter participatory governance filter should address. Scopus covers a wide range of publications but does not cover all publications in Web of Science, Google Scholar, or regional databases, which may affect estimates of geographic representation. Future work should replicate this analysis with broader database coverage, extend the temporal window as the 2025-2026 acceleration data become complete, and use co-citation network analysis (Cobo et al., 2011) to create higher-resolution maps of the field’s theoretical foundations.

DATA AVAILABILITY

The data supporting this study are available at <https://doi.org/10.17605/OSF.IO/72MV3>. The repository contains the following files:

- S1 – Raw Scopus Export: full metadata for all 684 initially retrieved records (authors, title, year, source, abstract, author keywords, citations, DOI)
- S2 – PRISMA Screening Summary: stage-by-stage decision log showing all 217 excluded records with exclusion reason for each of the three criteria
- S3 – Thematic Cluster Definitions: VOSviewer cluster assignments for all 892 unique author keywords, with cluster labels, representative keywords, and descriptions
- S4 – Performance Outcome Domains: the six-domain classification framework with full lexicons (8–14 terms per domain), theoretical grounding, and paper counts
- S5 – Cross-Classification Matrix: 467×6 paper-by-outcome domain assignment table showing all 540 cross-classified connections
- S6 – Search Strategy and Codebook: full Boolean search string, field specifications, inclusion/exclusion rules, inter-rater reliability protocol (Cohen’s $\kappa = 0.84$), and keyword-matching procedure

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHORS



Wachiranun Pum is an instructor at the Faculty of Management Science and Information Technology, Nakhon Phanom University, Thailand. She holds a bachelor's degree in computer science from Ubon Ratchathani University and a master's degree in computer science and information technology from Khon Kaen University, Thailand. Currently, she is pursuing a Ph.D. in IT Management at the Division of Information System Management Technology, Faculty of Engineering, Mahidol University, Thailand. Her research interests include computer science, marketing technology, and digital technology innovation. Her interdisciplinary approach combines technical knowledge with marketing applications to develop effective digital solutions for modern business challenges.



Narongsak Sukma is a Lecturer and Researcher at Siam Technology College. As a distinguished and highly dedicated academic, he holds three doctoral degrees: a Doctor of Public Administration and a Ph.D. in Information Technology Management from Mahidol University, alongside a Ph.D. in Computer Science from Naresuan University. With over 20 years of experience in information technology management, Dr. Sukma has worked across diverse industries, including Financial, banking, logistics, and telecommunications. He is a results-driven leader known for his expertise in IT governance, IT risk management, IT compliance, and the strategic application of advanced technologies. His innovative approaches enable businesses to harness the power of AI and big data, aligning Education technology solutions.



Adisorn Leelasantitham received the B.Eng. degree in Electronics and Telecommunications and the M.Eng. degree in Electrical Engineering from King Mongkut's University of Technology Thonburi (KMUTT), Thailand, in 1997 and 1999, respectively. He received his Ph.D. degree in Electrical Engineering from Sirindhorn International Institute of Technology (SIIT), Thammasat University, Thailand, in 2005. He is currently the Associate Professor in Technology of Information System Management Division, Faculty of Engineering, Mahidol University, Thailand. His research interests include applications of blockchain technology, conceptual models and frameworks for IT management, disruptive innovation, image processing, AI, neural networks, machine learning, quantum computing, IoT platforms, data analytics, chaos systems, and healthcare IT. He is a member of the IEEE.