Artificial Intelligence (AI) and Machine Learning (ML) in Marketing: A 25-year bibliometric-TCCM synthesized mapping of trends, gaps and future research agenda

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Abstract
This study provides a comprehensive 25-year review (2001-2025) of 439 publications on Artificial Intelligence (AI) and Machine Learning (ML) in marketing, combining bibliometric analysis with the Theories-Contexts-Characteristics-Methodologies (TCCM) framework. The analysis reveals three key observations: (1) exponential growth (13.05% annually) concentrated post-2017, with India, China, and US contributing 31% of publications; (2) four research clusters (digital marketing ethics, emerging markets, technical applications, consumer behavior); and (3) ten prominent theories. These findings are spread across three interconnected planes, namely, adoption (micro-level), value-creation (meso-level), and governance (macro-level). We identify critical gaps: underrepresentation of B2B, SME, and healthcare contexts; methodological over-reliance on quantitative approaches; and limited theoretical integration across levels. Building on these findings, we propose six testable propositions, introduce three novel constructs (Algorithmic Marketing Agency, Algorithmic Trust and Continuous Learning Loop Capability). An integrated conceptual framework is presented. Lastly, the study offers theoretical extensions to adoption, value-creation, and governance theories, and practical guidance through an AI/ML marketing application decision tree.

Key Words: Artificial Intelligence (AI); Machine Learning (ML); bibliometric study; Theories, Contexts, Characteristics, and Methodologies (TCCM)

JEL Code: M31; L36; D83

1. Introduction

Artificial Intelligence (AI) has been defined as the broader concept of machines designed to perform tasks that typically require human intelligence, while machine learning is a subset of AI focused on algorithms that enable computers to learn from and make decisions based on data (Riandhi *et al.,* 2025; Liu *et al.*, 2024). Due to this, it matters today because customers expect personalisation and speed, it improves efficiency, return on investment, and competitive edge and unlocks new capabilities (such as content generation and real-time optimization) (Khan *et al.*, 2025). The advent of these technologies in digital marketing in the past couple of decades has been marked with a shift from manual reporting to automated, learning systems shaping customer experience (Mohammed, 2025; Carrasco-García *et al.*, 2025; Shabankareh *et al.*, 2025). This has been observed with move from basic rules and analytics, to big data and supervised learning, to deep learning to today's foundation models, and real time personalisation (Dutta & Kannan Poyil, 2025). The ever need of hyper personalisation is fuelled from the explosion of large consumer generated data and it requires optimised techniques for managing large data set to make actionable decisions (Abbas & Al-Lawati, 2025). These are the enablers of the artificial intelligence, machine learning, computer vision tools in the digital marketing applications (Brahma & Revi, 2024).

There are adoption differences across various industries including retail, finance and healthcare. North America, Europe and other developed economies there is higher adoption in large firms as compared to the smaller ones. The integration of these technologies have changed the way marketing campaign are carried out, reaching and connecting to the target audience allowing them to experince personalised offerings and overall loyalty (Sriprasadh *et al.*, 2024). Now it is essential for the businesses to deliver more relevant, efficient, and scalable customer experiences to remain meaningful in the current business environment, the businesse are exploiting disruptive technologies to efficintly manage the marketing programs and drive maximum outcome (Brahma & Revi, 2024; Singh *et al.*, 2023). The AI-driven tools allows digital marketers to deep dive into customer insights to make favorable strategies, automaing repetitive routine tasks and managing overall customer engagement and satisfaction in the total digital landscape (Liu *et al.*, 2024).

The research on the AI's role within marketing has susbtantially increased in the last decade, that shows both technological advancements and essence of technological intervention in all aspects of marketing. This growing literatutre in the research domain of AI in marketing contains multiple important subdomains of marketing such as customer relationship management (Ramya *et al.*, 2024), programmatic advertising (Zou *et al.*, 2020), and AI-driven content creation (Aberathne & Walgampaya, 2021). However, despite this proliferation, the literature remains fragmented in terms of theoretical foundation, methodological approaches, and contextual focuses. The literature is more inclined towards one particular segment of marketing rather a cmprehensive mapping, it shows the importance of a research that not only maps the intellectual landscape but also identifies conceptual and empirical gaps in the research of adoption and application of AI in marketing. To fill this needed gap, the current study deploys a dual approach: a bibliometric analysis along with network analysis to visualize and quantify the structure and development of AI-marketing research, and the Theory-Context-Characteristics-Methodology (TCCM) framework to systematically evaluate the literature and propose future research directions (Mathews-Hunt, 2016).

The bibliometric techniques offer a descriptive strategy to evaluate research productivity, influence, and thematic clusters (Lin, 2025), the TCCM framework provides a comprehensive tool to evaluate theoretical development, contextual relevance, specific characteristics, and methodological consistency. Key areas that are less researched in the study of artificial intelligence and machine learning in marketing include generative artificial intelligence and creative marketing, customer experience beyond personalisation, cross-channel orchestration, SME adoption, ethics, bias, and explainability in practice. However, the existing studies have methodological (over reliance on archival or digital trace data, with limited longitudinal investigations), theoretical (lesser theoretical development linked to consumer psychology and organisational behaviour), and application (more focused on retail industry than any other industry and healthcare being less studied) limitations. The integration of artificial intelligence and machine learning in marketing enhances effectiveness through data driven support, fast and more precise decision making. In addition, it enables personalisation at large scale level, yield actionable insights, and continuous optimisation.

This study aims to answer the following key research questions by utilising the bibliometric and TCCM techniques:

1. *What are the intellectual foundations such as annual publication, most influential documents, most prolific authors, most contributing country etc. and emerging themes in AI marketing literature*?
2. *What are the key theoretical, contextual, characteristical and methodological dimensions of the research in AI in marketing applications*?
3. *What are the probable research directions for future expansion of the understanding of AI in marketing applications*?

The uniqueness of the current study lies in integrating bibliometric analysis with the TCCM framework, which enables not only the identification of structural knowledge patterns in AI/ML marketing research but also a deeper theoretical and methodological diagnosis of the field's evolution, fragmentation, and future trajectory. Futhermore, this study is contemporary, provides practical and theoretical insights across-disciplinary perspectives. The rest of the paper is organised as follows: research methodology is presented in next section that is followed by the results and discussion, then future research directions are presented which are followed by the conclusion.

2. Methodology

2.1 Search Strategy and Screening Protocol

This review followed PRISMA 2020 guidelines (Page et al., 2021) to ensure methodological rigor and reproducibility. On March 10, 2025, we searched the Scopus database using the following Boolean string in TITLE-ABS-KEY fields:

("machine learning" OR "deep learning" OR "artificial intelligence" OR "predictive analytics")
AND
("marketing" OR "digital marketing" OR "consumer behavior" OR "advertising")

Inclusion criteria: Peer-reviewed journal articles, conference papers, and book chapters (2001-2025), English language, with primary focus on ML/AI adoption/application in marketing contexts.

Exclusion criteria: Non-English publications; editorials/notes/surveys; purely technical studies without marketing application; duplicates.

Screening procedure: Two independent reviewers conducted title/abstract screening followed by full-text assessment. Disagreements were resolved through discussion. Studies were excluded if: (1) research questions focused solely on ML model performance metrics, (2) empirical analysis used non-marketing data without marketing outcome implications, or (3) marketing theory/practice implications were absent.

The PRISMA flow diagram (Figure 1) summarizes the screening process: 778 initial records → 439 final publications.

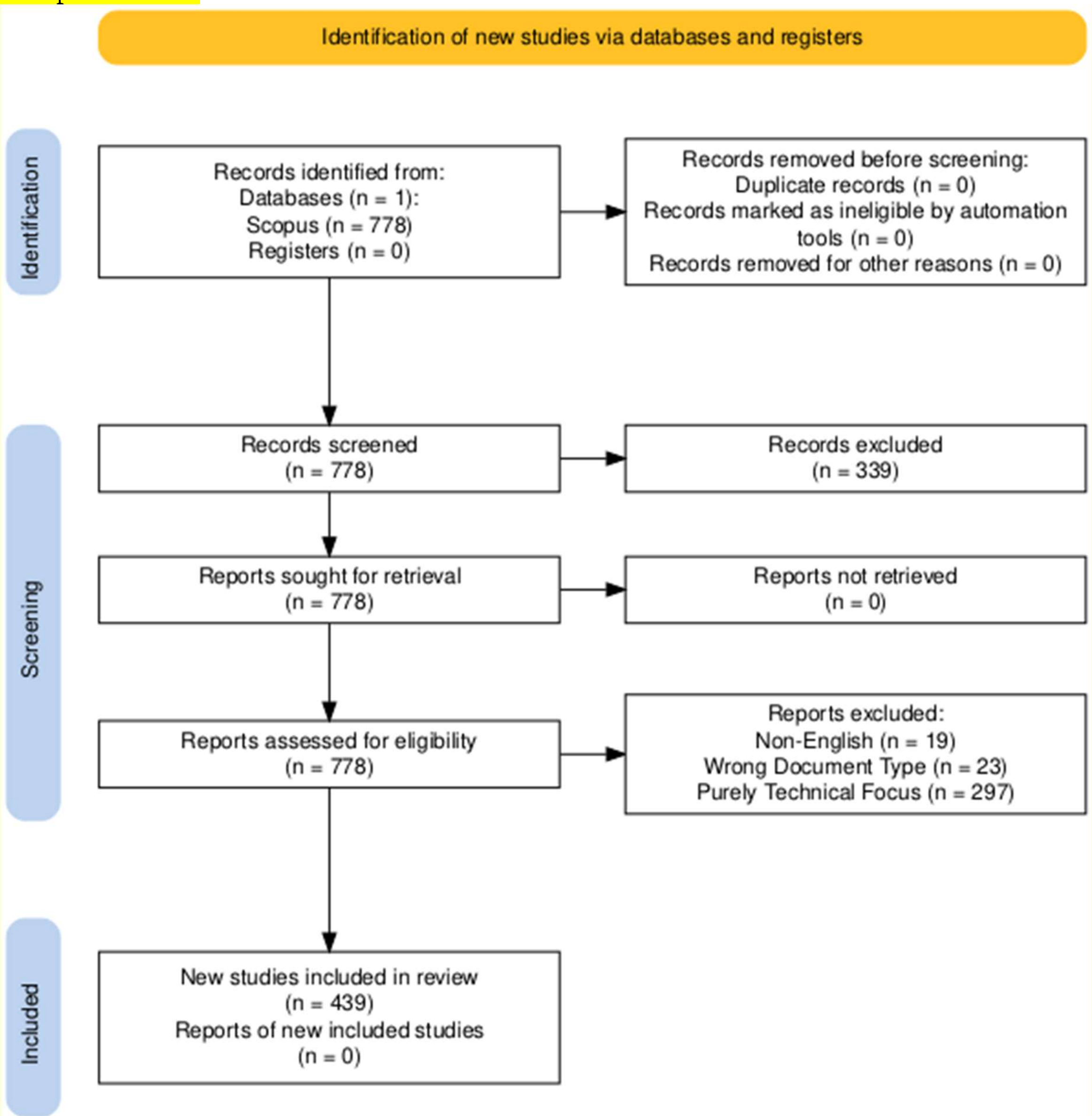


Figure 1: PRISMA 2020 flow diagram illustrating the identification, screening, eligibility, and inclusion process for the bibliometric-TCCM review of AI/ML in marketing (2001–2025)
Source: Authors' conception (2025).

2.2 **Analytical Approach**

We employed a three-stage mixed-methods design (Table 1):

- **Stage 1: Bibliometric Analysis** using Biblioshiny (R package) to map publication trends, influential documents, authors, and geographical distribution (Donthu et al., 2021).

- **Stage 2: Network Analysis** using VOSviewer to visualize co-authorship patterns and keyword co-occurrence clusters (Selim et al., 2022).
- **Stage 3: TCCM Analysis** applying Paul and Rosado-Serrano's (2019) framework to systematically evaluate theoretical foundations, contexts, characteristics, and methodologies.

Table 1: The systematic research methodology process

Step	Purpose	Tools Used	Key Activities	Outcome
1. Data Extraction	Search and identify relevant publications	Scopus Search Engine	Boolean keyword search in TITLE-ABS-KEY; download metadata	Initial dataset of 778 documents
2. Data Cleaning and Screening	Filter dataset to retain high-relevance publications	Excel, Manual Review	Remove non-English (19), exclude irrelevant document types (23), eliminate purely technical studies (297)	Refined dataset of 439 documents
3. Bibliometric Analysis	Explore publication trends and scientific mapping	Biblioshiny (R)	Analyze annual trends; identify top papers, authors, journals, geographical distribution	Snapshot of research productivity and influence
4. Network Analysis	Uncover co-authorship patterns and thematic clusters	VOSviewer	Keyword co-occurrence; author collaboration networks; cluster mapping	Identification of emerging themes and collaboration networks
5. TCCM Analysis	Assess depth and breadth of literature using TCCM framework	Python (Jupyter), Excel	Classify studies by theory, context, characteristics, methodology	Identification of research gaps and structured future directions

Source: Authors' conception (2025).

2.3 Data characteristics

The final dataset comprised 439 publications (2001-2025) from 318 sources, with 13.05% annual growth and 14.34 average citations per document. Authorship analysis revealed 1,426 authors (3.68 co-authors per document) and 17.92% international collaboration, indicating a maturing but still fragmented research community.

2.4 Network analysis

VOSviewer application is used for the network cluster creation to visualise the research landscape in the adoption and application of machine learning in marketing. It is one of most applied method in the visulation of scintific landscape of a given research domain (Selim et al., 2022). We conducted Co-authorship and keywords co-occurrence analysis to create intuitive maps to understand the current research paradigm.

2.5 TCCM analysis

The TCCM framework is widely used in systematic literature reviews point out the most widely used frameworks focusing on geography, culture and specific industries. Characteristics to understand predictors, moderators, mediators and outcomes of a particular study as well as methodologies used to explore the phenemenon. This method helps in analysisng the literature in depth and stressing on the areas which need further expolaration and attention of the scholars. The python script was used on the Jupyter platform (a python web service) to identify the TCCM components followed by excel spreadsheet to prepare tables for presentation.

3. Results

3.1 Bibliometric Analysis: Mapping the Intellectual Landscape

Analysis of 439 publications (2001-2025) reveals three defining characteristics of AI/ML marketing research (Table 2).

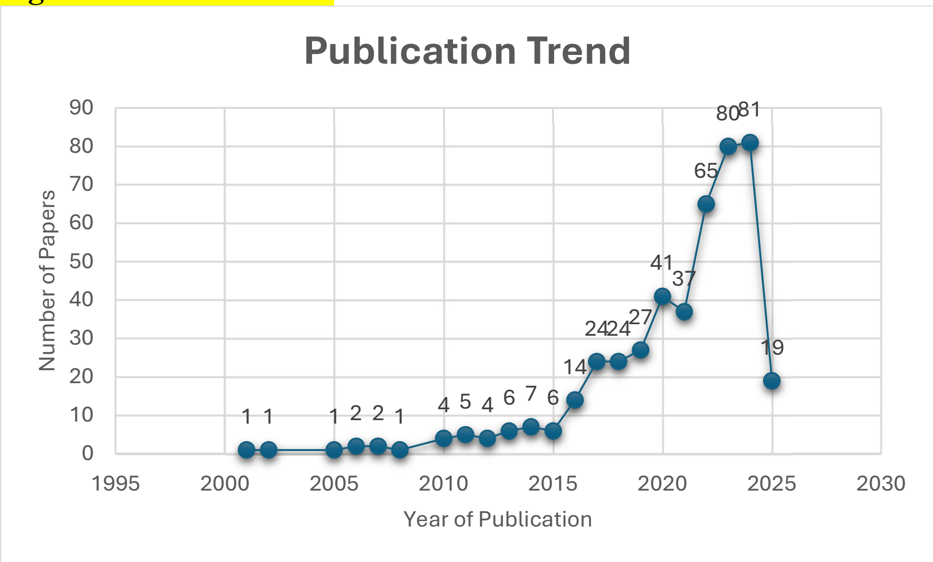
Table 2: Data characteristics

Main information about data	
Timespan	2001:2025
Sources (Journals, Books, etc)	318
Documents	439
Annual Growth Rate %	13.05
Document Average Age	4.39
Average citations per doc	14.34
Keywords Plus (ID)	2564
Author's Keywords (DE)	1303
Authors	1426
Authors of single-authored docs	45
Single-authored docs	45
Co-Authors per document	3.68
International co-authorships %	17.92
article	166
book	4
book chapter	22
conference paper	245
conference review	2

Source: Authors' conception (2025).

Growth trajectory: The field exhibits 13.05% annual growth, with publications concentrated in the post-2017 period (Figure 2). This acceleration coincides with advances in deep learning and increased industry AI investment. The decline observed in 2025 reflects partial-year data rather than reduced scholarly interest.

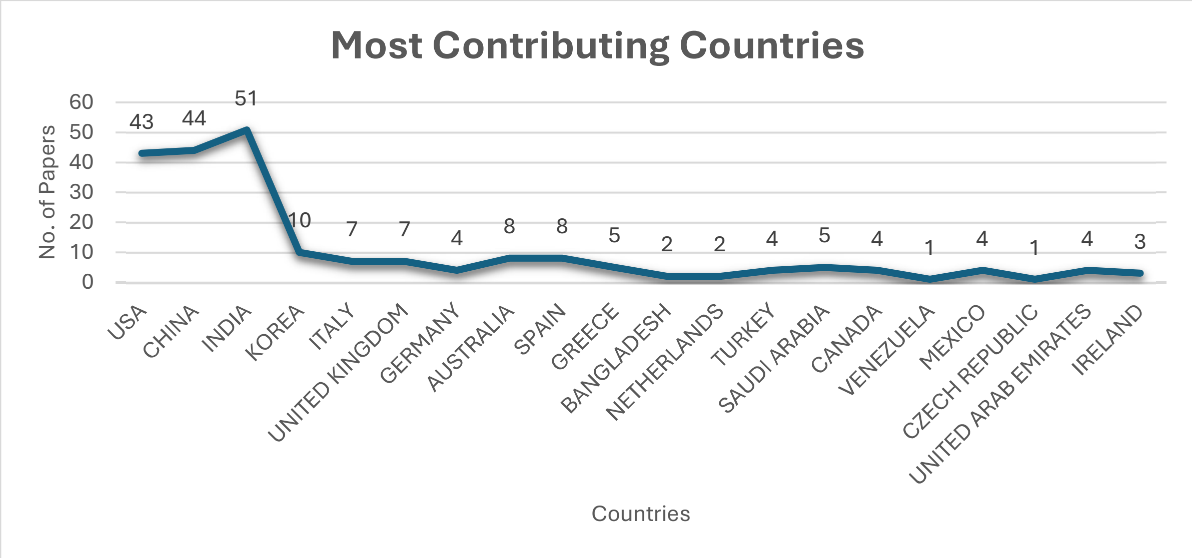
Figure 2: Publication trend



Source: Authors' conception (2025).

Geographic concentration: Research output is highly concentrated in three countries, India (51), China (44) and USA (43) which collectively account for 31% of publications (Figure 3). This geographic skew reflects structural advantages in data availability, computational infrastructure, and university-industry partnerships rather than purely intellectual interest. Notably, contributions from African, Latin American, and smaller Asian economies remain marginal, suggesting knowledge production inequalities that future research should address.

Figure 3: Most Contributing Countries



Source: Authors' conception (2025).

Authorship patterns: The field demonstrates strong collaboration (3.68 co-authors per document) but modest international co-authorship (17.92%), indicating primarily national/regional research networks. Top authors by h-index (Tang J, Zhang W, Zhang Y) differ from those by citation count (Xu T, Nair HS, Hosanagar K) (Table 3), suggesting that highly productive authors are not necessarily the most influential—a pattern consistent with emerging fields where multiple research streams develop in parallel.

Table 3: Top 10 authors

Based on h-index		**Based on Total Citations**		**Based on No. of papers**	
Author	***h*_index**	**Author**	**TC**	**Author**	**NP**
TANG J	5	XU T	1008	ZHANG W	7
ZHANG W	5	NAIR HS	672	CHEN X	6
ZHANG Y	5	HOSANAGAR K	666	WANG L	6
CHEN X	4	LEE D	666	ZHANG Y	6
LI Q	4	PAN J	549	WANG J	5
REN K	4	SHI Y	547	TANG J	5
WANG J	4	HE X	515	XU Z	5
WANG L	4	ATALLAH A	504	SHARMA A	5
XU J	4	BOWERS S	504	XU J	5
XU Z	4	CANDELA JQ	504	LI Q	5

Source: Authors' conception (2025).

Influential works: The most cited paper (Lee et al., 2018, 666 citations) examines Facebook advertising content and consumer engagement, reflecting sustained interest in social media marketing applications (Table 4). Notably, 8 of the top 10 cited papers address advertising-specific applications (real-time bidding, click prediction, ad fraud), indicating that digital advertising has been the primary empirical context driving theoretical development.

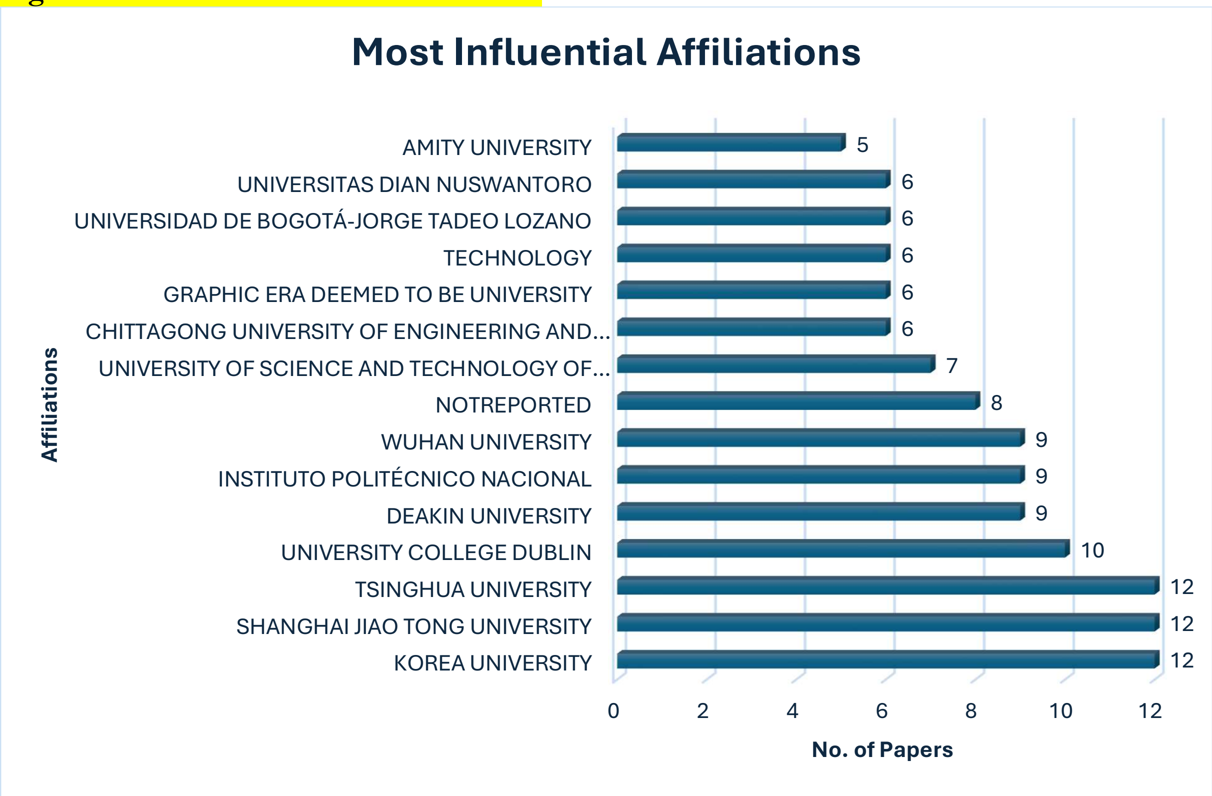
Table 4: Ten Most Influential Documents

Paper	Year	Title	Source	Total Citations
Lee D	2018	Advertising content and consumer engagement on social media: Evidence from Facebook	Management Science	666
He X	2014	Practical lessons from predicting clicks on ads at Facebook	Proceedings of the Eighth International Workshop on Data Mining for Online Advertising	504
Cai H	2017	Real-time bidding by reinforcement learning in display advertising	Proceedings of the Tenth ACM International Conference on Web Search and Data Mining	173
Adamopoulos P	2018	The impact of user personality traits on word of mouth: Text-mining social media platforms	Information Systems Research	164
Chen X	2019	Information diffusion prediction via recurrent cascades convolution	IEEE 35th international conference on data engineering	163
Kim JW	2001	Application of decision-tree induction techniques to personalized advertisements on internet storefronts	International Journal of Electronic Commerce	152
Hadiji F	2014	Predicting player churns in the wild	IEEE conference on computational intelligence and games	139
Crussell J	2014	Madfraud: Investigating ad fraud in android applications	Proceedings of the 12th annual international conference on Mobile systems, applications, and services	137
Perlich C	2012	Bid optimizing and inventory scoring in targeted online advertising	Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining	125
Radesky J	2020	Digital advertising to children	PEDIATRICS	106

Source: Authors' conception (2025).

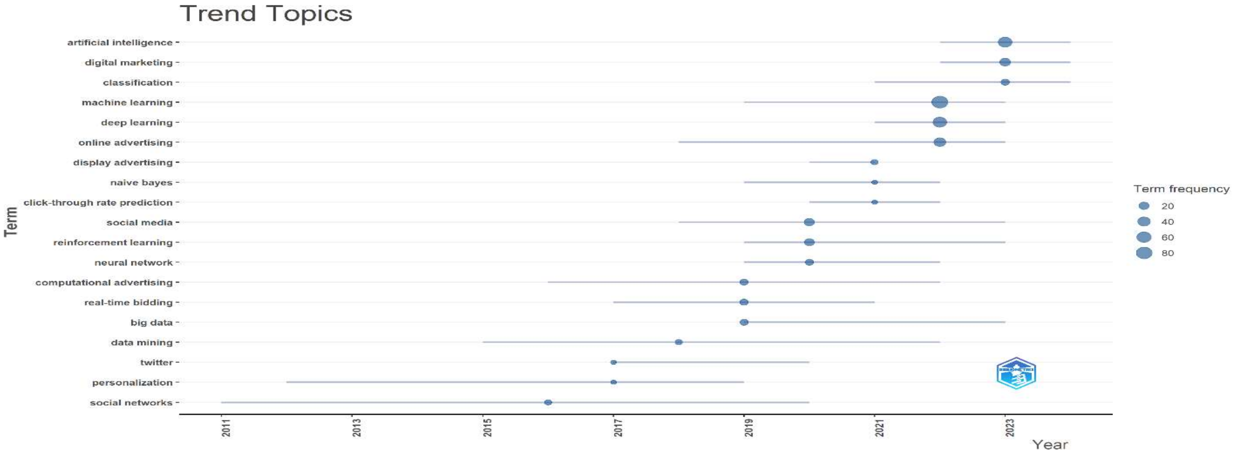
Institutional landscape: Korea University, Shanghai Jiao Tong University, and Tsinghua University lead in publication volume (Figure 4), but productivity differences are modest (range: 5-12 publications). This suggests the field remains open to new entrants without entrenched institutional hierarchies.

Figure 4: Fifteen most influential affiliations



Source: Authors' conception (2025).

Figure 5: Trend topics



Source: Authors' conception (2025).

Thematic evolution: Trend topic analysis (Figure 5) reveals a clear shift from foundational methods (decision trees, SVM, 2011-2015) to contemporary concerns (deep learning, reinforcement learning, 2020-2024). The emergence of "artificial intelligence" as the dominant term post-2022 signals broadening beyond narrow ML applications toward integrated AI marketing systems. The word cloud (Figure 6) confirms marketing, machine learning, and artificial intelligence as core concepts, with advertising, deep learning, and learning systems as secondary clusters.

Figure 6: Word cloud for research themes

Source: Authors' conception (2025).

3.1.1 Evolution of Machine Learning Algorithm Keywords in Marketing Research

We performed a temporal analysis of algorithm-specific terms in order to address the thematic diversity revealed by the high count of Keywords Plus (n=2564) and Authors Keywords (n=1303). The information shows a distinct shift in methodological emphasis.

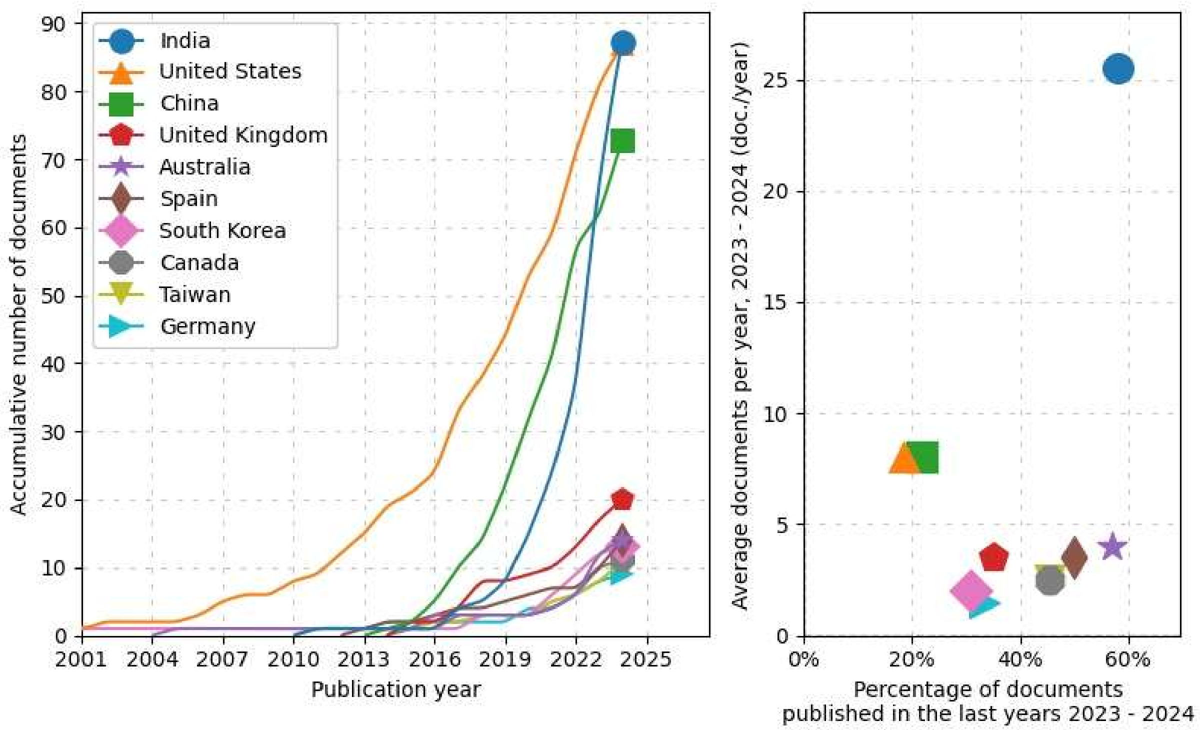
Early Period (2001–2010): Basic methods like decision trees (e.g., Kim et al., 2001), regression and clustering are frequently used in customer relationship management for segmentation and simple predictive tasks.

Growth Period (2011–2017): As interest in click-through rate prediction and digital advertising optimization grew so did the rise of support vector machines (SVM), random forests and early neural networks (e.g., Perlich et al., 2012).

Current Period (2018–2025): Advanced methods such as deep learning, natural language processing (NLP), reinforcement learning and transformer models have become increasingly popular during this period. These align with new research areas in multi-touchpoint attribution, sentiment analysis, real-time personalization and generative AI for content.

As noted in our thematic clusters (Section 3. 3), this development reflects the wider transition in marketing from descriptive and predictive analytics to prescriptive and generative AI applications. From generic machine learning to named architectures like BERT and GANs algorithm keywords are becoming more specific, indicating a developing field where methodological sophistication is increasingly connected to marketing outcome variables.

Figure 7: Accumulative increase in publications



Source: Authors' conception (2025).

Figure 7 above depicted in two parts, presents the accumulation of publications over a 24 year period (2001-2025) and the average documents per year from 2023-2024. It is observed that the United States has produced publications within the research domain almost every year with the exception of 2025. It should be noted that, as much as these two countries individually have produced significantly more documents on average compared to the other countries, those other countries have actually produced higher percentages of documents within the same period. The remaining 7 countries had less than 5 publications each with percentages ranging from 30 to 60%.

3.1.2 Critical Interpretation of Bibliometric Findings

While the bibliometric analysis identifies growth trajectories, dominant countries and influential authors as well as thematic clusters, these patterns also highlight the importance of AI/ML marketing literature to various fields explored in this resarch. Firstly, the concentration of highly cited work within digital advertising contexts suggests that theoretical development in AI/ML marketing has been excessively driven by performance-oriented advertising optimization problems. This them introduces the theoretical implication that knowledge in the field is heavily influenced by environments rich in data like social media rather than marketing phenomena such as relationship development and B2B ecosystems. This could therefore result in the current theories not fully reflecting generalizable marketing principles. Secondly, the geographic concentration of publications in India, China and the United States is not necessarily a reflection of research productivity but a result of these countries having a significantly higher amount of resources in compararison to other nations. As a result, the intellectual trajectory of the field may be influenced by contexts characterized by high digital maturity, potentially limiting theoretical transferability to emerging or resource-constrained economies.

3.2 Network analysis

A network analysis was conducted to examine co-authorship structures and collaboration patterns in AI/ML marketing research to provide insights into knowledge diffusion and institutional connectivity within the field. This was done to enhance descriptive bibliometric indicators.

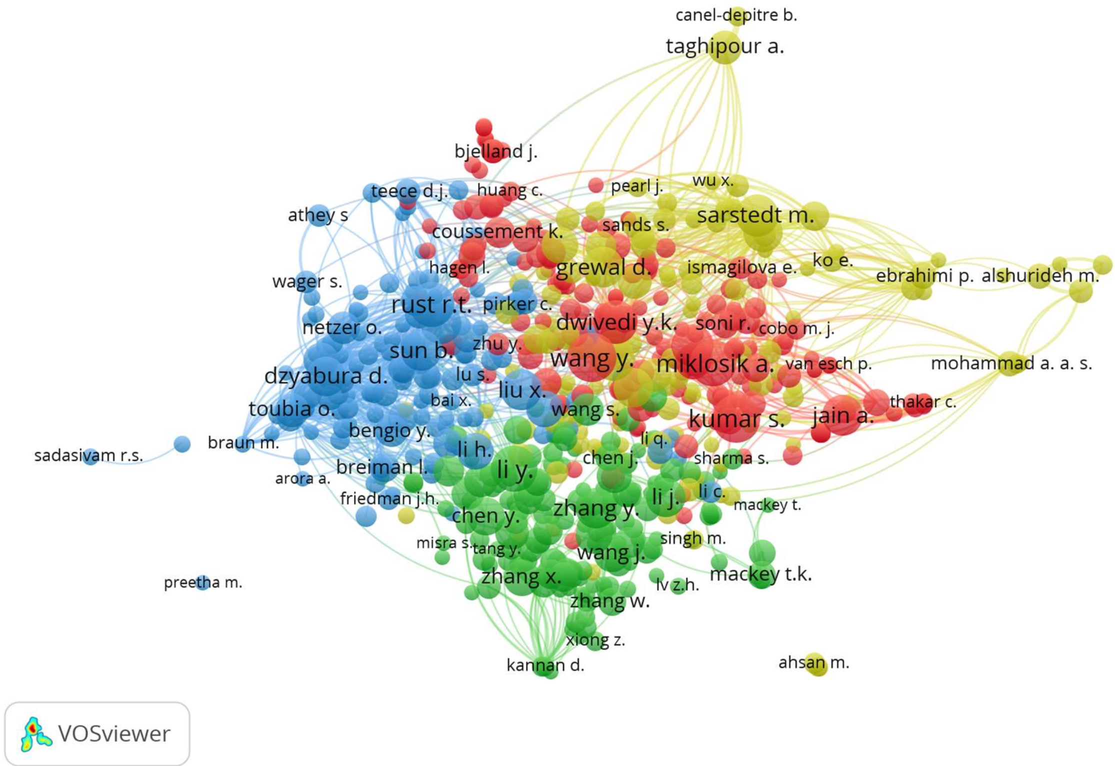


Figure 8: Co-authorship analysis
Source: Authors' conception (2025).

3.3 Co-authorship analysis

Using VOSviewer with thresholds of minimum 3 articles and 5 citations per author, the co-authorship network resulted in four distinct research clusters (Figure 8) which is reflecting the intellectual structure of AI/ML marketing research landscape.

Cluster 1 (Red - Digital Marketing and Ethics, n=181 authors): Dominated by Dwivedi, Ismagilova, and Alshurideh, this cluster investigates critical ethical dimensions of AI adoption—data privacy, algorithmic bias, and consumer trust in automated marketing (Alkhazaleh & Al-Dwiry, 2018; Wasiq et al., 2024). Research here emphasizes transparency and accountability in AI-driven customer interactions, including metaverse marketing applications (Arya et al., 2023; Dwivedi et al., 2022).

Cluster 2 (Green - Emerging Markets and Cross-Cultural Studies, n=162 authors): Centered on scholars like Wang, Zhang, and Ebrahimi, this cluster examines how cultural, economic, and infrastructural factors moderate ML effectiveness in developing economies (Chattopadhyay et al., 2023). Key themes include cross-cultural consumer segmentation, localization of global ML algorithms, and mobile-commerce acceleration (Zhang et al., 2025).

Cluster 3 (Blue - Technical ML Applications, n=143 authors): Featuring authors such as Bengio, Friedman, and Huang, this cluster focuses on algorithmic development—neural networks, deep learning, and predictive modeling—for specific marketing functions including ad targeting, real-time behavioral intelligence, and decision optimization (Radesky et al., 2020; Youngmann et al., 2021).

Cluster 4 (Yellow - Consumer Behavior and Personalization, n=132 authors): Led by Rust, Grewal, and Sarstedt, this smallest cluster applies ML techniques to analyze complex consumer preferences and enable hyper-personalization through sentiment analysis, dynamic pricing, and recommendation engines (Kim et al., 2025; Qiu et al., 2024).

3.4 Keywords C-occurrence analysis

Keyword co-occurrence analysis (minimum frequency =10) resulted in three thematic clusters (Figure 9) which is revealing the conceptual structure of the field:

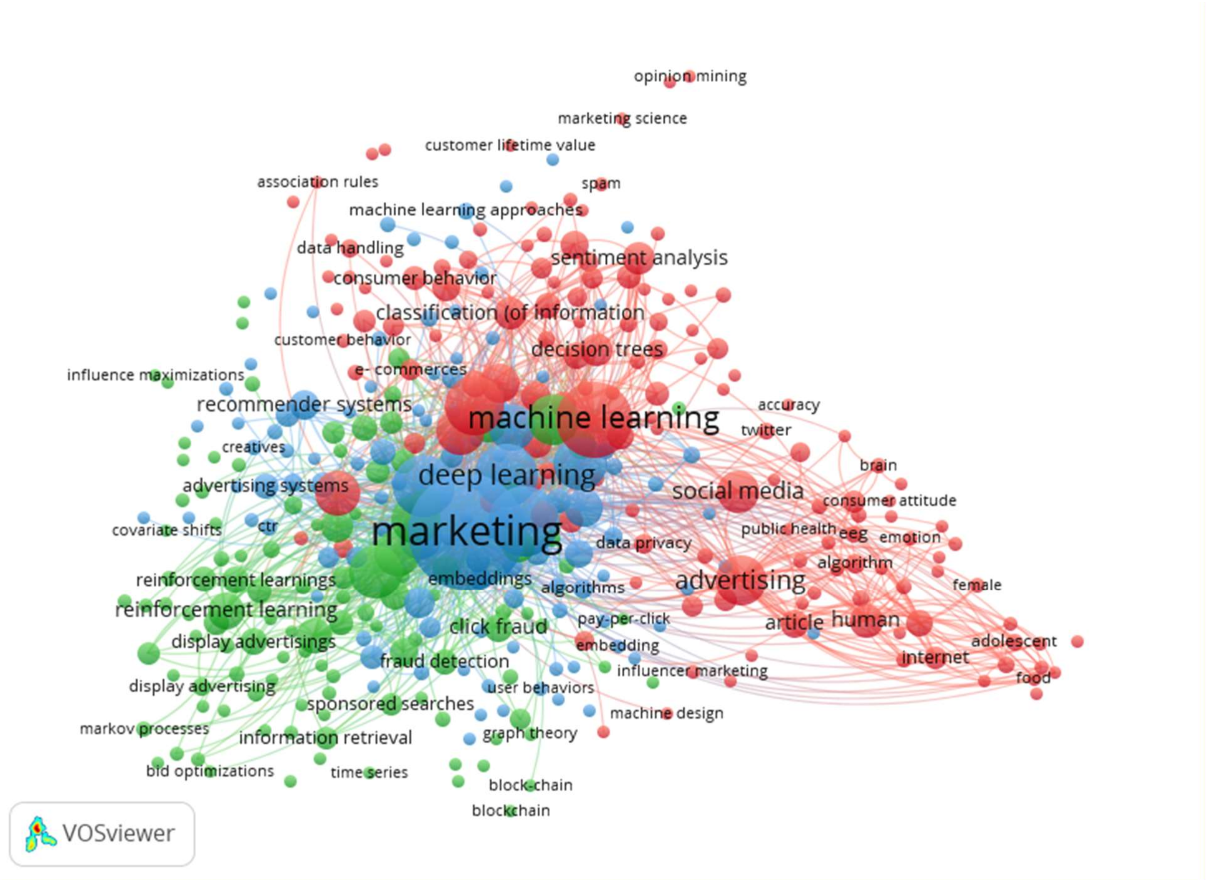


Figure 9: Keywords C-occurrence Analysis
Source: Authors' conception (2025).

Cluster 1 (Red - Consumer Analytics, 144 keywords): Dominated by terms including consumer behavior, sentiment analysis, decision trees, deep learning, and predictive modeling, this cluster represents ML applications for customer insight generation—specifically segmentation (Thakkar, 2024), churn prediction (Gulnara et al., 2024), and customer lifetime value optimization (Abidar et al., 2023).

Cluster 2 (Green - Digital Advertising, 115 keywords): Centered on reinforcement learning, recommender systems, display advertising, and bid optimization, this cluster captures ML's role in ad placement, content optimization, and fraud detection in pay-per-click campaigns (Alzahrani et al., 2025; Guo & Jiang, 2025).

Cluster 3 (Blue - Data Privacy and Governance, 111 keywords): Featuring data privacy, algorithmic accountability, covariate shifts, and embeddings, this emerging cluster addresses privacy-preserving ML, bias mitigation, and ethical considerations in AI-driven marketing (Sharma & Sharma, 2023; White et al., 2020).

3.5 TCCM Framework

Based on Paul and Rosado-Serrano (2019), we analyzed the theoretical, contextual, characteristic and methodological dimensions of AI/ML marketing research to identify gaps and future directions.

3.5.1 Theoretical Foundations: Toward an Integrated Multi-Level Framework

Analysis reveals 10 prominent theories spanning micro, meso, and macro levels (Table 5). However, the key insight is not their presence but their *relationships*:

While Table 5 presents the ten prominent theories individually, their true explanatory power emerges through integration. These theories do not operate in isolation but form three interconnected analytical planes: (1) adoption-diffusion theories (TAM, UTAUT, TPB, DoI) explaining technology acceptance at the micro-level; (2) value-creation theories (RBV, SDL, Dynamic Capabilities) explaining competitive advantage at the meso-level; and (3) governance-trust theories (Signaling, Institutional, ECT) explaining legitimacy at the macro-level. The phenomenon of AI/ML in marketing sits at the intersection of all three planes—consumers must adopt AI tools (Plane 1), firms must derive advantage from them (Plane 2), and both must navigate trust and accountability concerns (Plane 3). Future theory development must address these intersections rather than treating each theory as a standalone explanatory framework.

Table 5: Ten most prominent theories

Theory Name	Frequency	Conceptual Focus	Application in ML Marketing	Strengths in Literature	Key Weaknesses	How This Theory Connects to Others
Technology Acceptance Model (TAM)	34	Tech adoption & usage behavior	Evaluates user intention to adopt ML tools and recommender systems	Predictive power, widely validated, easy to use	Ignores social/contextual factors	Foundation for adoption plane; connects to UTAUT (comprehensive adoption) and ECT (post-adoption satisfaction)
Unified Theory of Acceptance and Use of Technology (UTAUT)	22	Tech adoption under social influence	Assesses ML-based tools adoption under moderating influences	Comprehensive; includes social & facilitating factors	Complex, low parsimony	Extends TAM by adding social influences; bridges adoption (Plane 1) with institutional pressures (Plane 3)
Theory of Planned Behavior (TPB)	18	Behavioral intention & control	Studies consumer decision-making influenced by ML predictions	Strong psychological foundation	Less predictive in dynamic digital environments	Links individual adoption (Plane 1) to actual behavior; connects to ECT in continuance decisions
Resource-Based View (RBV)	16	Competitive advantage from internal resources	Evaluates how ML capabilities become strategic assets	Strategic depth, firm-level focus	Hard to operationalize capabilities	Core of value-creation plane (Plane 2); connects to Dynamic Capabilities (adaptation) and SDL (co-creation)
Diffusion of Innovations (DoI)	14	Tech spread and adoption stages	Analyzes spread of ML tools across	Good for longitudinal studies	Lacks predictive modeling	Bridges adoption (Plane 1) and diffusion across contexts; connects

			industries or consumer segments			to Institutional Theory (normative pressures)
Information Processing Theory	12	Cognitive decision-making process	Explores how ML helps consumers process complex information	Explains individual-level marketing response	Overly individual-centric	Micro-foundation for both adoption (Plane 1) and algorithmic trust (Plane 3)
Expectation Confirmation Theory (ECT)	11	Post-adoption satisfaction	ML's role in shaping satisfaction and repurchase behavior	Good for loyalty and retention studies	Focuses on post-adoption, less on adoption	Links adoption (Plane 1) to loyalty outcomes; connects to Trust perceptions (Plane 3)
Signaling Theory	10	Reducing information asymmetry	Explains ML's use in pricing signals, trust indicators in e-commerce	Useful in online trust-building contexts	Ambiguity in signal interpretation	Core of governance plane (Plane 3); connects to TAM (trust as usefulness antecedent)
Service-Dominant Logic (SDL)	9	Value co-creation	Analyzes ML-enabled personalization as co-creation of value	Customer-centric, integrative	Still evolving; limited quantitative testing	Links value-creation (Plane 2) to customer experience; connects to Trust (Plane 3) in co-creation contexts
Institutional Theory	8	Institutional pressures and legitimacy	How firms adopt ML in response to mimetic/coercive/normative pressures	Explains external influence on firm behavior	Less focus on individual or technical dimensions	Macro-level governance (Plane 3); explains why firms adopt AI (connects to DoI, RBV)

Source: Literature Review (2025).

- **Micro-level theories** (TAM, UTAUT, TPB, Information Processing) share an *adoption-centric* paradigm—they ask why humans accept AI tools, not how AI systems shape human choices before acceptance occurs. This creates a **temporal blind spot**: by the time a consumer "adopts" AI, the AI has already structured the choice architecture.

- **Meso-level theories** (RBV, DoI, Dynamic Capabilities) treat AI as a *resource* to be acquired, overlooking AI's *generative* nature—models improve through use, creating capabilities that cannot be owned in traditional senses.

- **Macro-level theories** (Institutional, Signaling) address external pressures but rarely connect to algorithmic design choices.

Theoretical gap: No existing theory adequately captures AI's *dual nature* as both tool and agent. This motivates our proposed **Algorithmic Marketing Agency (AMA)** construct (developed in Section 3.7).

3.5.2 Contextual Landscape: Concentration and Neglect

While AI/ML research spans 10 contexts (Table 6), three dominate: e-commerce, social media, and banking/financial services. Neglected contexts include:

- B2B marketing: Only 10% of studies examine B2B contexts, despite AI's potential for account-based marketing and relationship lifecycle management
- Healthcare: Growing but still underrepresented post-COVID
- SMEs: Research assumes enterprise-level resources, ignoring SME constraints
- Public sector/nonprofit: Virtually absent despite AI's potential for social marketing

Contextual implication: Theory developed in dominant contexts may not generalize. Future research must test boundary conditions through systematic cross-contextual comparison.

Table 6: The dominant Contexts

Sl. No	Context Type	Description	Rationale for ML Use	Observed Trends
1	E-commerce	Online retail, product recommendations	Personalization, dynamic pricing	Dominant application area
2	Social Media Marketing	Content targeting, sentiment analysis	ML for engagement optimization	Rapid growth in influencer targeting
3	Banking & Financial Services	Customer churn, fraud detection, credit scoring	Predictive modeling, risk management	High security and compliance needs
4	Healthcare Marketing	Patient targeting, pharmaceutical campaigns	AI-driven targeting and ethical concerns	Increasing post-COVID
5	Retail (offline/omni-channel)	In-store personalization, loyalty programs	ML-driven consumer profiling	Integration of ML with IoT
6	Hospitality & Tourism	Customer service, review mining	Forecasting demand and satisfaction	Experiential marketing strategies
7	Education (EdTech)	Learner segmentation, engagement strategies	Adaptive learning and targeting	Emerging domain
8	Government & Public Policy	Public campaign targeting, behavioral nudges	Predictive behavioral insights	Data privacy sensitivity
9	Logistics & Supply Chain	Inventory forecasting, route optimization	Optimization via ML analytics	Operational efficiency
10	B2B Marketing	Account-based marketing, lead scoring	ML for relationship lifecycle	Niche but growing

Source: Literature Review (2025).

3.5.3 Characteristic Structure: Antecedents-Mechanisms-Outcomes

Synthesizing across studies, we identify a consistent causal architecture (Figure 10):

Antecedents (data inputs: IoT, CRM, social media, surveys) → Mediators (ML mechanisms: algorithms, segmentation, predictive models) → Outcomes (marketing performance: sales, retention, ROI, CX). This structure is moderated by organizational (firm size, skills, budget) and environmental (market dynamics, regulations, ethics) factors. The field has focused heavily on antecedents-outcomes relationships while treating mediating mechanisms as a "black box." Future research must open this box by examining which algorithms produce which outcomes which conditions that a research agenda requiring collaboration between marketing scholars and computer scientists.

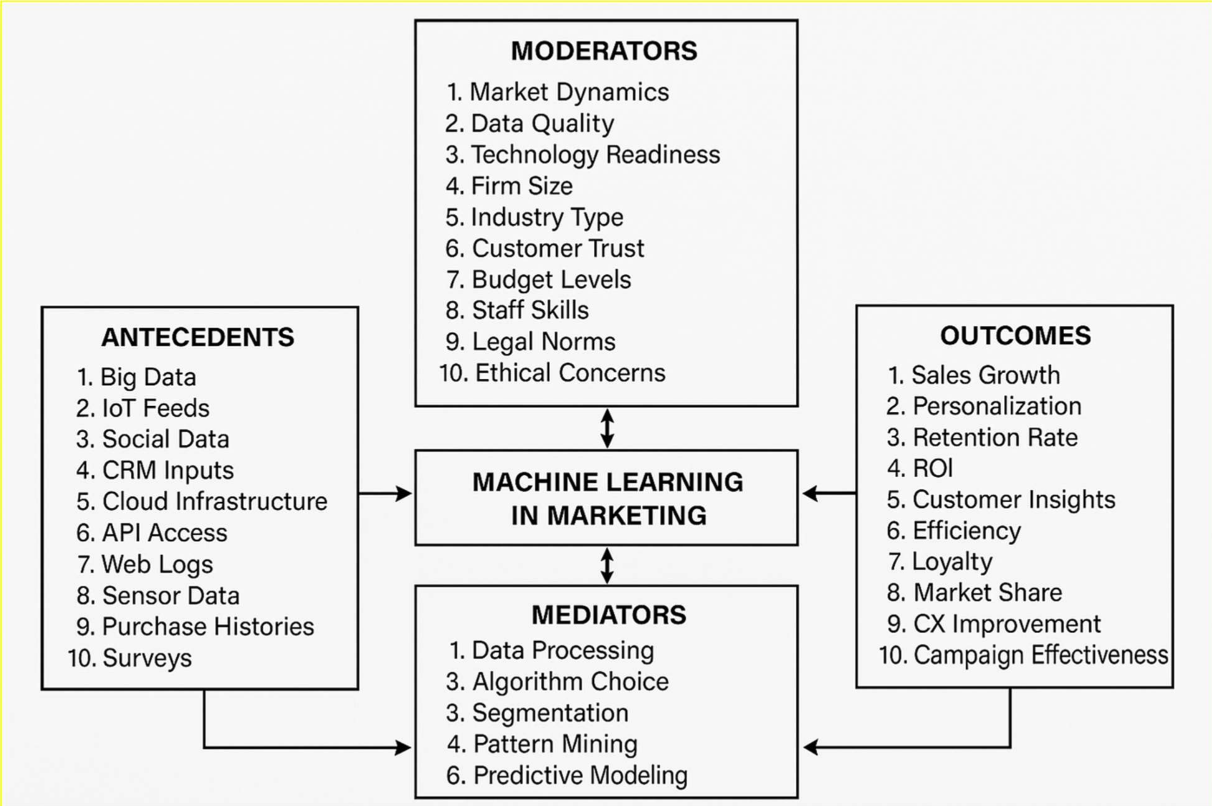


Figure 10: Antecedents, mediators, moderators, and outcomes in the adoption of ML in marketing.
Source: Authors' conception (2025).

3.5.4 Methodological Profile: Quantitative Dominance, Qualitative Neglect

Methodological analysis (Table 7) reveals heavy reliance on quantitative primary data and secondary/big data analysis (65% of studies). Qualitative, mixed, and action research methods remain marginal (<15%). This creates three limitations:

- Process understanding: We know what AI does, but not how it changes organizational practices or consumer experiences
- Contextual depth: Quantitative studies abstract from context, limiting transferability
- Theory building: Inductive theory development is rare, explaining the field's reliance on imported theories (TAM, RBV) rather than indigenous theory

Table 7: Ten prominent methodologies

Method Type	**Description**	**Relevance in ML Marketing**	**Tools & Example**
Quantitative (Primary Data)	Surveys, experiments, and behavioral data combined with ML models.	Customer segmentation, churn prediction, CLV modeling.	Tools: Python (scikit-learn, TensorFlow), R, SQL. Examples: Sentiment analysis on survey data, RFM + clustering.

Secondary Data / Big Data	Leveraging existing datasets (logs, CRM, social media) for ML-driven insights.	Real-time personalization, recommendation systems.	Tools: Hadoop, Spark, Google Analytics. Examples: Clickstream analysis, NLP on Twitter data.
Experimental Design (A/B Testing)	Controlled experiments to test ML-driven campaigns, pricing, or ad variations.	Optimizing ad creatives, dynamic pricing models.	Tools: Optimizely, Google Optimize. Examples: Testing ML-powered vs. rule-based recommendations.
Qualitative Methods	Interviews, focus groups to explore perceptions of AI/ML in marketing.	Early-stage adoption studies, ethical concerns.	Tools: NVivo, ATLAS.ti. Examples: Consumer trust in AI chatbots.
Mixed Methods	Combining surveys (quantitative) with interviews (qualitative) for holistic insights.	Validating ML models with human judgment.	Examples: Survey + interview study on AI-powered customer service.
Case Study	Deep insights into firms successfully implementing ML in marketing.	Best practices, ROI measurement.	Examples: Netflix's recommendation engine, Amazon's dynamic pricing.
Simulation / Agent-Based Modeling	Simulating market dynamics & consumer behavior under ML-driven strategies.	Testing "what-if" scenarios before deployment.	Tools: NetLogo, AnyLogic. Examples: Simulating viral ML-driven ad campaigns.
Systematic Review / Meta-Analysis	Comprehensive mapping of findings from ML-marketing literature.	Identifying trends, gaps, and future directions.	Tools: PRISMA, VOSviewer. Examples: Review of AI in digital marketing (2015–2024).
Action Research	Iterative ML implementation in real-world marketing teams.	Organizational adoption of AI/ML.	Examples: Implementing and refining a chatbot in a B2C firm.
Ethnographic / Netnographic	Observational studies of how consumers interact with ML-driven marketing.	Cultural nuances in AI adoption.	Examples: Studying Reddit communities' reactions to AI-generated ads.

Source: Literature Review (2025).

Methodological implication: The field needs methodological pluralism—qualitative studies of AI implementation processes, ethnographic research on consumer-AI interaction, action research on organizational adoption.

Synthesizing across the TCCM dimensions we have presented a unified theoretical picture as AI/ML in marketing is best understood as a multi-level phenomenon which requires multi-theoretical lenses. At the micro-level, adoption theories explain initial engagement while at the meso-level, value-creation theories explain capability development. Moreover, at the macro-level, governance theories explain legitimacy and trust. These levels are not independent adoption that enables value creation, which generates data that requires governance which in turn shapes future adoption. Future research should explicitly test these cross-level interactions rather than examining each theoretical plane in isolation. Our conceptual framework (Figure 12) and testable propositions (P_1-P_6) operationalize this integrated perspective.

4. Theoretical Implications

Building on the bibliometric patterns and TCCM analysis, this study advances three conceptually grounded constructs that extend existing marketing theory. These constructs are inductively derived from recurrent empirical themes observed across 439 publications over 25 years, rather than proposed as a priori theoretical extensions. The AMA is conceptualized as an integrative construct that draws on multiple bibliometric clusters, namely autonomous learning systems, real-time personalization, and ethical governance. This therefore captures the evolution of AI-driven marketing systems toward autonomous, learning-based and accountable decision-making.

A key theoretical contribution of this study is the identification of new constructs. These may be considered as an extension of existing marketing theories. While the study introduces AMA where AI/ML systems autonomously generate insights, the Algorithmic Trust and Fairness Perception is conceptualized as assessment of the transparency and ethicality of AI-driven marketing decisions. Further, the study advances the construct of Continuous Learning Loop Capability that integrates real-time data feedback into adaptive marketing strategies through AI/ML systems. These constructs extend multiple theoretical streams simultaneously. AMA advances consumer behavior and decision-making theories acknowledging that choices are increasingly influenced by recommendations. Algorithmic Trust and Fairness Perception extend TAM, TPB, and Signaling Theory. It highlights that the perceived usefulness is not sufficient in AI enabled environments. It must accompany trust and ethical legitimacy. Continuous Learning Loop Capability expands RBV and Dynamic Capabilities Theory by explaining how firms sustain competitive advantage through ongoing algorithmic adaptation rather than static resource ownership.

The results in this study change fundamental academic discourses by placing AI and ML as main influential elements on techno-functional fluidity. While previous literature treated digital environments as auxiliary or transactional, this study frames them as primary experience spaces. The theoretical foundations used in the recent research based on the adoption of AI/ML in marketing the ten most frequently used theories, have been unearthed and advanced. These have been identified as TAM, UTAUT, TPB, RBV, DoI, Information Processing Theory, ECT, Signalling Theory, SDL, and Institutional Theory. These theories cover broad perspectives including individual and organisational behaviour. This study shows AI and ML are transforming marketing theory, challenging existing ideas and creating new perspectives.

(a) *Marketing Theory:* AI/ML-driven personalization, dynamic pricing, and predictive targeting have changed the traditional marketing frameworks. While the 4Ps are based on product, price, place, and promotion, AI/ML relies on adaptation of these elements in real time. Therefore theories based on consumer behavior models and predictive analytics are providing insights into decision-making and reshaping theories of brand loyalty, customer journey mapping, etc (Bruni et al., 2022). Similarly, SDL framework views service as the fundamental basis of exchange, where operant resources (skills, knowledge, relationships, etc.), and operands (things, artifacts, etc.), can be visualised as the primary factors in value co-creation (Ra et al., 2023). The metaverse provides an environment in integrating haptic and 3D presence to enhance the experience as the bibliometric mapping revealed a strong association in marketing, Human-Computer Interaction (HCI), and psychology. The convergence of customer experience with human skills, personalization, processes, etc. was evident and implies that the classical theories should be revisited for adaptation of marketing mixes and brand engagement.

(b) *Technology Adoption and Diffusion Theory:* The TAM and UTAUT are centered on the usefulness and ease of use (Heriyati et al., 2025). The determinants of adoption of technology and in the context of metaverse it is not confined to the efficiency but also to experiential value, ease in navigation, social connectivity etc (Bilquise et al., 2024). Emerging research suggests that the TAM must be expanded with new constructs focused on trust, interaction quality, presence and immersion, etc. The other influencing factors may be identified as the privacy, personalization quality, and digital well-being that essentially impacts the adoption (Neuhofer, 2025). In AI/ML contexts, perceived usefulness and experiential outcomes are derived from trust, fairness, immersion, and personalization (R & Demiris, 2024). Similarly, innovation diffusion theory assess the organizational readiness, consumer adoption, transparency, and ethical safeguards to succeed (Kasmon et al., 2025). The broad implication of adoption and diffusion theories is to integrate algorithmic trust, data privacy, and perceived fairness as antecedents in AI/ML adoption.

(c) *Data-Driven Analytics, Organizational and Strategic Theories:* AI/ML contributes significantly to data-driven marketing theories as predictive and prescriptive modeling creates new constructs that are associated with data maturity, marketing dynamics and performance (G et al., 2023). Theories of marketing intelligence should therefore evolve to accommodate automated pattern recognition, adaptive learning loops, and predictive foresight as key drivers of performance (Dalal & Singh, 2024). Therefore, data-driven frameworks should theorize how analytics capabilities co-evolve with organizational maturity, producing new pathways for customer insight and competitive advantage. From a RBV, AI/ML constitutes not just technological assets but strategic capabilities that enable sustained advantage (Ahmad-Fauzi & Md Saad, 2024). Dynamic capabilities theory is similarly extended as firms use algorithmic agility, data infrastructure, and cross-functional integration to reconfigure marketing strategies in real time (Barta et al., 2024). Strategic marketing theories, such as relationship marketing and competitive positioning, are being reframed by AI-mediated collaboration and adaptive decision-making autonomy (Sb et al., 2024). Strategic and organizational theories should theorize AI/ML as both operant resources and dynamic enablers that enhance marketing agility, collaboration, and positioning.

(d) *Consumer and Behavioral Theory:* AI is reshaping consumer behavior through recommendation and personalization. In this case the decisions are not linear but mostly influenced by AI algorithms (Dalal & Singh, 2024). The touchpoint theory traditionally conceptualizes CX as a sequence of firm–customer interactions during the customer journey (Baxendale et al., 2015). The application is not limited to physical stores, websites, or call centers only but now it is applied to the context of metaverse avatar-to-avatar interactions, engagements with AI brand agents, participation in immersive events, and co-creation. Moreover, the fluidity of touchpoints heavily depends on technological infrastructures, trust, and experiential factors and therefore in the context of metaverse, the touchpoint theory underlines the transition of CX from a linear to a dynamic and experiential framework (Baxendale et al., 2015). In this context, the flow theory and presence theory also offer insights into AI-enabled environments that deepen immersion and engagement. It explains the psychological state of users with complete absorption and deep immersion (Tw et al., 2025). As the barriers and glitches are rising to disrupt the experience, behavioral theories should expand to model AI as an effective determiner in shaping consumer journeys. It must emphasize over trust, fairness, and algorithm-mediated perceptions of value.

(e) *Innovation and Knowledge Theory:* AI/ML transforms innovation and knowledge sharing through collaboration and feedback. Also, customer interactions create real-time insights that algorithms use to learn and adapt. This shows innovation adoption is dynamic, not static, and fits with theories of organizations that continuously learn and adapt (K-S et al., 2025). Co-creation now involves both humans and AI algorithms, changing how knowledge is created and shared in marketing. Theories of innovation and knowledge need to include AI-driven co-creation, automated feedback, and dynamic learning as key parts of marketing innovation.

These insights provide fertile ground for proposition-building and future empirical testing. The major gaps include: (1) bridging TAM's cognitive-rational acceptance variables with affective mechanisms of Flow and Presence to explain both adoption and deep engagement; (2) mapping non-linear touchpoints with resource integration processes through SDL and (3) exploring antecedents and moderators as a flow-facilitator or disruptor. Practically, this integrated framework assists in formulation of propositions that would help understand the phenomena through mixed methods. The current bibliometric and TCCM-guided analysis led to the discovery of major theoretical advances. It introduces emerging antecedents are Big Data and IoT Feeds largely generated from real-time inputs, social data, mediators being data processing methods used in cleaning the data and preparing the data ready-for-use, algorithm choice to make selection of appropriate ML techniques such as neural networks, decision trees, market dynamics and industry type, data quality and technology readiness, firm size and budget levels, staff skills and customer trust, legal norms and ethical concerns are viewed as the moderators. Outcome variables are sales growth, ROI, and market share, customer behavior and needs, retention rate and loyalty for better engagement.

4. Contributions to Practice

Strategically, AI algorithms and ML are designed to support business models, in a way reducing human error, ensuring audience data efficiency and scaling advertising (Haleem, Javaid, Qadri, Singh & Suman, 2022). This ultimately enhances marketing decision-making and strategic planning. In addition, AI allows for monitoring of market trends (Al-Surmi, Bashiri & Koliousis, 2022). It also detects anomalies and opportunities (Edozie, Shuaibu, Sadiq & John, 2025) which would result in improved operational performance (Al-Surmi *et al.,* 2022). Integrated AI, ML and marketing applications support SDG 12 which is focused on Responsible Consumption and Production, ensuring that engagement does not exploit psychological vulnerabilities. Furthermore, marketers could measure the ROI or effectiveness of AI/ML-based interventions through experiments in controlled environments where the impact of AI/ML is isolated and empirically tested (Kumar, VAshraf & Nadeem, 2024). Organizations could benchmark best practices in AI by observing what their peers are implementing within the same industry or through assessing industry reports as well as published reputable studies (Amoako, Omari, Kumi, Agbemabiase & Asamoah, 2021). Management in organizations could encourage data-driven marketing through the creation of dedicated marketing teams for AI implementation as this could be key to enhancing business performance (Thompson & Laney, 2020). It could therefore be suggested that marketing professionals, policy makers and researchers leverage findings to tailor campaigns that prioritize experiential engagement, such as branded virtual events or gamified interactions. These strategies not only improve customer retention but also foster long-term brand relationships in ways that are sustainable over time and value-driven (Patel, 2024). The AI driven digital tools allow marketers to deep dive into customer insights to make favourable strategies, automating repetitive routine tasks and managing overall customer engagement and satisfaction in the total digital landscape (Liu *et al.*, 2024).

The AI/ML Marketing Application Decision Tree presented in Fig 11 offers marketers a methodical framework for matching relevant data-driven solutions with their marketing objectives. The first step is to identify the main goals which could include automation personalization campaign optimization customer insights or predictive analytics. Following that marketers receive guidance on important factors like data accessibility, financial constraints, technical know-how schedule and regulatory requirements. According to these variables the model recommends a range of approaches. Such as basic analytics or hybrid phased approaches to sophisticated deep learning with real-time personalization. To guarantee the long-term and successful integration of AI/ML into marketing strategies it concludes by highlighting a four-step implementation process: data audit resource planning pilot testing and scaling.

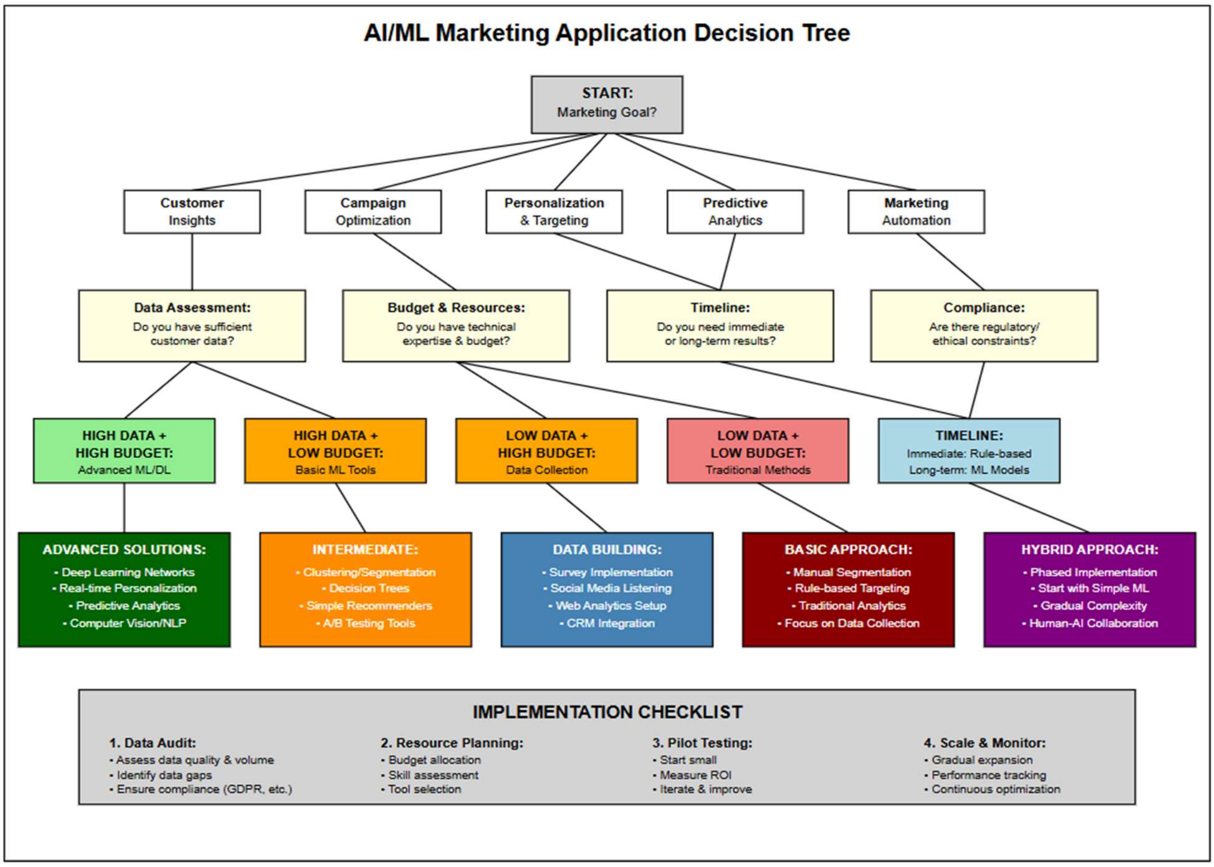


Figure 11: AI/ML Marketing applications (Decision Tree).
Source: Authors' conception (2025).

5. Justification of Novel Contributions

Notwithstanding the high growth of review studies on AI in marketing, prior studies remain fragmented in scope, limited in depth, rigour and largely descriptive in nature, thereby constraining cumulative theory development. Existing bibliometric reviews generally focus on minor subdomains, short time horizons, or AI as a monolithic construct, often overlooking machine learning a different and theoretically meaningful research stream (Thakur & Kushwaha, 2023; Ziakis & Vlachopoulou, 2023). While insightful, the conceptual papers similarly and often lack longitudinal scientometric evidence to systematically trace the intellectual evolution of AI and ML in marketing (Ngai et al., 2022). Filling these gaps, the present research brings a new 25 year bibliometric-TCCM synthesized mapping that integrates theory-driven qualitative interpretation with quantitative science-mapping techniques. Unlike the research studies before, the current research captures long term epistemic evolution of AI and ML research in marketing, clearly differentiates AI and ML centric intellectual trajectories, and organises extant knowledge across theoretical foundations, core constructs, contextual settings and methodological approaches. Moving beyond descriptive clustering toward an integrated TCCM framework, the article uniquely bridges bibliometric evidence with theory building, identifies persistent blind spots such as heterogeneity of context, methodological imbalance, ethical governance among others. Further to this, it develops a forward-looking research agenda grounded in both intellectual structure and empirical trends. Due to this, the work advances the AI-ML marketing literature from fragmented reviews toward a theory informed, coherent and future oriented knowledge source fit for high impact scholarly discourse.

6. Conclusion and limitations

In conclusion, bibliometric techniques offer a descriptive strategy to evaluate research productivity, influence and thematic clusters while the TCCM framework provides a comprehensive tool to evaluate theoretical development and contextual relevance. The TCCM also provides specific characteristics, and methodological consistency. Possible limitations of the currently adopted integrated methodology include data source restrictions, citation-based biases, limited theoretical insights and superficial engagement, underemphasis on practical relevance and overly prescriptive structures. However, regardless of the amount of prior published work on integrated AI, ML and marketing applications based on common primary and secondary research methodologies, some of the least used approaches can be used predictively in future to explore deeper insights in this domain. Researchers can apply scientometrics, altimetrics, content analysis and topic modelling, citation analysis, co-authorship and collaboration analysis, text mining, network analysis, bibliographic coupling, temporal or evolutionary analysis. These approaches can be achieved through relevant tools such as Dimensions.ai, LDA, BERT, Gephi, Pajek etc. On the other hand, the TCCM approach can help map out the growth of the research area, showing which topics, theories, and authors are shaping the field and help explore the new avenues in this domain.

7. Direction for future research

In the current study, we encourage future researchers to utilize alternative methodologies to address and answer relevant questions in the area. Focusing on hyper personalization, using Deep Learning (DL) for enhancing individual targeting with transformer-based models related to adjusting and modifying real time to user behaviour. Emotionally conscious marketing such as the use of AI to evaluate customer emotions from multimodal data and tailor making marketing content. , of campaigns.

Artificial intelligence ethics, privacy and fairness in marketing, thus using bias detection methodologies in digital advertising algorithms, which may include how ML reinforces societal biases and how to reduce them in digital advertising efforts and digital marketing campaigns. To add to this, federated learning for privacy-conscious personalization, and explainable artificial intelligence for marketing decision making using black box models interpretable to managers and compliance with regulation. Conversational Artificial Intelligence and customer engagement need to be adopted, by checking on how advanced chatbots and virtual assistants can be used for automated customer service and product discovery in electronic commerce and digital marketing. Image and voice search optimization for more enhanced customer interaction, and human-AI in sales mainly focusing on trust, persuasion, and effectiveness.

Future researchers can go an extra mile in investigation of AI generated ads, slogans, and visuals can influence customer perceptions and brand equity. A/B testing of synthetic content for generation and optimization of multiple content variations autonomously, as well as managing and identifying virtual brand ambassadors vs synthetic influencers. Using NLP for social listening to detect shifting sentiments, brand threats and emerging trends from unstructured online data. Mapping, classifying and clustering ecosystems of competitors using unsupervised public open data, and scenario simulation tools application to test digital marketing strategies. Decision support for Artificial Intelligence-augmented marketing. This may include but is not limited to campaign planning using cognitive automation for designing, executing and refining strategies, modelling digital twin of the customer for insights and experimentation, examining AI and human decision synergy. Application of multimodal ML for unified customer reviews, cross channel attribution, Internet of Things (IoT) and smart environments (smart homes and digital retailing). Promotion and dynamic pricing through Reinforcement Learning (RL), real time customer segmentation and context-aware (location, time, device and mood) marketing.

7.1 Conceptual Model

Based on a thorough analysis of 439 publications the conceptual model is presented in Fig 12, it offers a methodical framework for comprehending AI/ML integration in marketing.

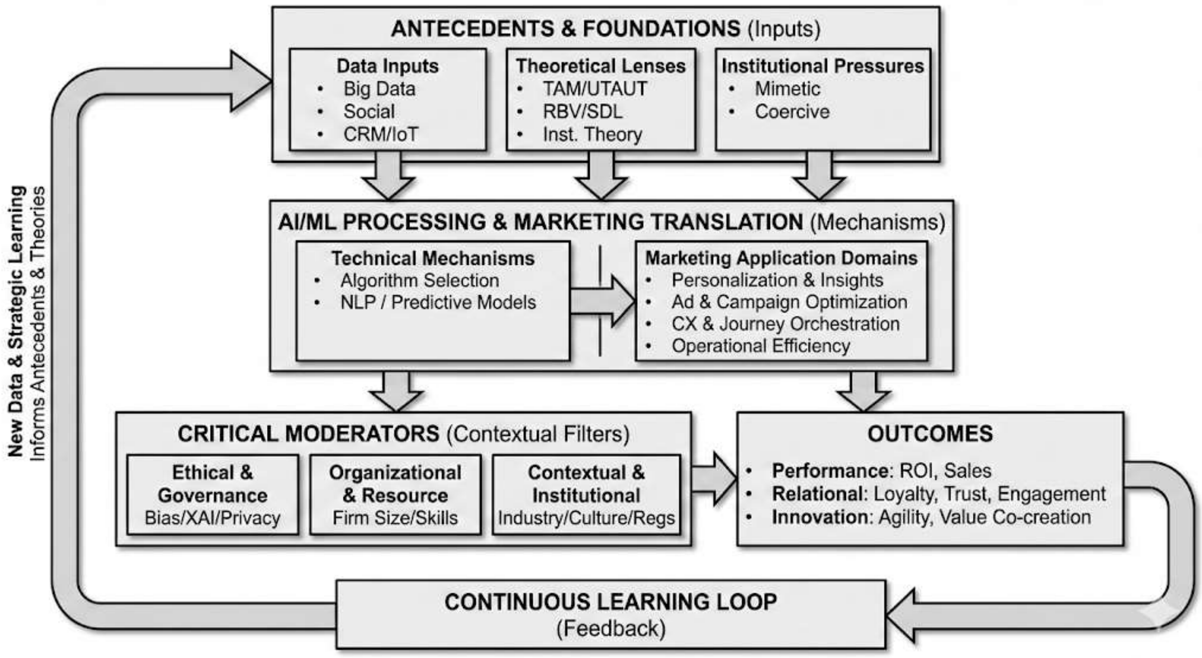


Figure 12: An integrated framework for AI/ML in marketing, synthesized from bibliometric and TCCM analysis (n=439)
Source: Authors' conception (2025).

An integrated framework for AI/ML in marketing, synthesized from bibliometric and TCCM analysis is presented in Fig 12 that offers marketers a methodical framework for matching relevant data-driven solutions with their marketing objectives. This integrated framework synthesizes 439 studies, and it shows a dynamic ecosystem where institutional pressures, data inputs and theoretical underpinnings drive the conversion of technical mechanisms into marketing applications. It highlights that in contrast to generic models the relationship between AI processing and strategic outcomes such as performance relational trust and innovation is not direct rather it is filtered through crucial moderators like organizational resources, ethical governance and contextual constraints. In order to keep the model flexible and reflect the details of the contemporary marketing environment this process ends in a continuous learning loop where new data and strategic insights are fed back into the foundational inputs.

7.1.1 Testable propositions for future research

To enhance the empirical applicability of our framework, six testable propositions have been developed which bridge theoretical constructs with measurable marketing variables. These propositions are directly grounded in the gaps and trends identified in our bibliometric and TCCM analysis. The six testable propositions (P_1–P6) are derived directly from the temporal trends and thematic clusters and TCCM gaps found in our analysis. In particular P_1 (personalization × privacy) results from the increasing co-occurrence of data privacy and personalization keywords in recent years (Fig. 5 & 9). The predominant Digital marketing and ethics research cluster (Section 3. 3) serves as the foundation for P_3 (algorithmic transparency → trust) and P5 (ethical governance → brand loyalty). While the Algorithmic Trust theoretical gap found in the TCCM analysis (Table 5). P_2 and P_4 are related to the increasing number of studies on real-time optimization and predictive analytics seen in the post-2020 publication trends (Fig. 2) whereas P2 tackles the developing but little-studied topic of generative AI found in our trend topics (Fig. 5). As a result, each claim converts a particular empirical gap or thematic priority from our bibliometric-TCCM mapping into a testable hypothesis for further empirical investigation.

P_1: *AI-driven personalization has a stronger positive effect on customer engagement when mediated by perceived relevance and moderated by data privacy concerns.*

P_2: *The adoption of ML-based predictive analytics in marketing significantly improves ROI, particularly when organizational data maturity and cross-functional integration are high.*

P_3: *Algorithmic transparency positively influences consumer trust in AI-recommended products, with effects amplified in high-involvement purchase contexts.*

P_4: R*eal-time ML optimization of marketing campaigns enhances customer experience, contingent upon infrastructure latency and IoT connectivity.*

P_5: *Ethical AI governance reduces consumer backlash and strengthens brand loyalty, especially in sensitive sectors (healthcare, finance, children's marketing).*

P_6: *The integration of generative AI in content creation improves marketing efficiency but may negatively affect brand authenticity if not balanced with human creativity.*

7.1.2 Empirical research questions

To guide future empirical studies, we propose the following research questions that operationalize our framework:

RQ_1: *How do different ML algorithms (e.g., neural networks vs. decision trees) perform across various marketing contexts (e.g., acquisition vs. retention campaigns)?*

RQ_2: *What organizational capabilities are necessary to translate AI/ML investments into sustainable competitive advantage in marketing?*

RQ$_3$: *How do consumers perceive and respond to AI-generated marketing content compared to human-created content across different demographic segments?*
RQ$_4$: *What are the most effective governance frameworks for ensuring ethical AI deployment in personalized marketing while maintaining performance?*
RQ$_5$: *How can SMEs overcome resource constraints to effectively implement AI/ML in their marketing operations?*

In the suggested conceptual modelling framework, inputs such as big data generated from IoT streams, customer relationship management (CRM) systems and social media interactions serve as primary indicators that are changed through AI and ML, including data pre-processing, neural networks, algorithm selection and predictive modelling (Bashar, Nyagadza *et al.*, 2025), into measurable outcomes for example ROI, sales growth, customer retention, and personalisation effectiveness (Davenport *et al.*, 2020; Zhai *et al.*, 2022). The strength of these linkages is contingent upon several moderating factors, such as data quality, firm size, employee analytical skills, market turbulence, and ethical governance structures (Verhoef *et al.*, 2021; Dwivedi *et al.*, 2021). More importantly, AI and ML are conceptualized in the current study as enabling analytical technologies, while domains such as social media marketing, electronic commerce, financial services, and emerging immersive or metaverse-related ecosystems are treated strictly as application contexts in which AI and ML capabilities are deployed, rather than as technological constructs themselves (Nyagadza *et al.*, 2025; Dwivedi *et al.*, 2021). The conceptual modelling framework is theoretically rooted in ten well-established perspectives frequently adopted in the marketing and information systems literature, including Institutional Theory and the TAM (Venkatesh *et al.*, 2003); Hair *et al.*, 2018). In line with the observed annual growth rate of approximately 13% in AI and ML related research, the conceptual modelling framework synthesizes insights from four dominant bibliometric clusters (Bashar, Alkadash *et al.*, 2025), such as ML applications, consumer behaviour, cross-cultural research, and digital marketing ethics, thereby offering researchers and practitioners a structured lens through which AI and ML driven capabilities can be systematically translated into marketing performance outcomes while accounting for contextual and governance-related contingencies (Davernport *et al.*, 2020; Zhai *et al.*, 2022). The proposed conceptual framework extends existing marketing theory. The framework is embedded with AI/ML mechanisms that are largely absent from previous models. Traditional frameworks treat analytics as linear input–output systems, whereas this model integrates continuous learning and ethical governance as core theoretical components. By doing so, the framework advances marketing theory from a predictive and reactive logic toward a self-adaptive and continuously optimizing paradigm. Here the marketing outcomes are derived through algorithmic decisions interacting with organizational and contextual moderators.

DECLARATIONS

Ethics approval

This article does not involve any studies with human participants or animals performed by any of the authors. Therefore, ethical approval was not required. All data and materials used in this work are publicly available or obtained through legal and ethical means.

Consent for publication

All authors consent publication of the article.

Availability of data and materials

Not applicable.

Competing interests

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Disclaimer

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Authors' contributions

Authors contributed equally to the development of the article.

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