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RESEARCH PAPER

From Segmentation to Hyper-Personalization: A Systematic Literature Review of AI-Enabled Marketing Strategies

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ABSTRACT

To trace how AI-enabled marketing strategies have evolved from traditional segmentation toward AI-enabled hyper-personalization, and to map the current evidence base along this trajectory. Marketing segmentation has progressed from rule-based demographic targeting through data-driven predictive clustering toward AI- and generative-AI-enabled hyper-personalization, yet prior reviews rarely trace this progression as a single evolutionary narrative. A PRISMA-guided review searched five open-access sources (Google Scholar, CORE, DOAJ, SSRN, Semantic Scholar) across 13 batches, screening 71 unique records verified against Crossref, DOAJ, CORE, and publisher metadata; 29 studies were retained across four evolutionary stages. AI-enabled personalization is increasingly linked to gains in engagement, retention, and conversion, but effectiveness-measurement standards remain unharmonized and privacy/algorithmic-bias concerns are largely unresolved. Adopt standardized effectiveness metrics, embed privacy and bias governance into personalization design from the outset, and expand subscription-database coverage of the Traditional and Emerging stages in future reviews.

Keywords: AI-enabled marketing, hyper-personalization, customer segmentation, systematic literature review, PRISMA

Introduction

The concept of marketing segmentation has been at the foundation of marketing since ever and it involves segmenting the customers as per their demographic, geographic or psychological attributes and tailoring different strategies to each of the different segments (Gajanova et al., 2019; Ali, 2016). This practice has evolved twice in the past 20 years: first, the opportunity to segment on the back of large amounts of behavioural and transactional data, which permitted segmentation at a lower level of granularity than just demographic data; and lately the very possibility of using Artificial Intelligence (AI) which is being promoted as an ability to reach the individual consumer level instead of the level of the segment (Desai, 2022; Guendouz, 2024).

This change of gears is often called “hyper-personalization” and can be seen as the logical next step in traditional personalization, made possible by the use of AI and machine learning technologies that can be directly applied to the segmentation, targeting and positioning (STP) process (Desai 2022). Guendouz (2024) uses this transition to anchor it in the larger context of an industrial transformation: moving away from Industry 4.0, with its mass customization, towards Industry 5.0, with its hyper-customization driven by AI. Davenport et al. (2020) was one of the first people to suggest an overall framework for thinking about how AI is working in marketing, categorizing its impacts based on the level of intelligence of the AI system, type of marketing function and the extent of embodiment—as well as warning that it's unlikely to replace a marketing manager.

Literature Review

This fast-moving area has been addressed by subsequent scholarship in an attempt to synthesize it. Vlačić et al. (2021) performed a systematic review of 164 peer-reviewed articles on pervasive AI in marketing, where the themes of segmentation, targeting, and positioning were among the most significant ones in marketing, but couldn't trace them as a specific evolutionary story. In this bibliometric study, Chandra et al. (2022) analysed 383 publications exclusively on personalized marketing and documented the existence of six thematic clusters of personalized marketing such as personalized recommendation systems and the so-called personalization–privacy paradox; he specifically called for the incorporation of AI and big-data analytics in the personalization of experiences in the future. While Kshetri (2023) outlined various uses, opportunities, and open areas and challenges for generative AI in interactive marketing, Peltier et al. (2024) conducted a review of more than 300 studies on 16 marketing journals to develop a conceptual framework for AI-enabled value co-creation in interactive marketing.

Beside this reviewed background several other publications are arranged side-by-side which are not systematic broad reviews of AI in marketing themselves. Osakwe et al. (2023) briefly examines literature pertaining to predictive analytics and customer segmentation in the context of digital marketing in particular, in the same continuum of segmentation to personalization that this review follows. As an initial step, Drăghici et al. (2023) and Peyravi et al. (2020) provide more general theoretical or historical coverage of the role of artificial intelligence and emerging technologies in marketing in general, covering the evolution of those studies that have been followed and paved the way for the AI-based personalisation literature included in the results. Madanchian (2024) and Gao et al. (2023) discuss narrow applied questions, about how AI marketing affects e-commerce sales, and about what ethical issues fulfill AI as a marketing effective measurement and the ethical dimensions of AI in advertising targeting, personalization and content creation, respectively, back to the effectiveness-measurement and ethics themes in the discussion.

What these prior reviews have in scope, and what this review adds, is a difference in framing rather than in raw subject matter: rather than treating AI-in-marketing or personalization as a single undifferentiated research area, this review organizes the included literature into four sequential stages that mirror the progression named in its title, from Traditional/Rule-Based Segmentation, through Data-Driven & Predictive Segmentation, to AI-Enabled Hyper-Personalization, and finally to Emerging/Future Directions. This staged framing makes it possible to ask not only what AI-enabled personalization looks like, but how the marketing strategies that produced it developed, and where the current literature's evidentiary weight actually sits.

(RQ1) What are the developments or evolutions in the approaches to market segmentation that have occurred over the last few years from rule-based segmentation to AI hyper-personalisation systems? What AI technologies and methods make the path towards AI-powered hyper-personalisation from data-driven segmentation possible? (RQ2). (RQ3) How does AI-based hyper-personalisation show differences from previous marketing segmentation methods in terms of strategies and results? (RQ4) What are emerging trends, gaps, and future directions of the current state of the literature? The Methodology section presents the methodology followed by the review (based on PRISMA) and describes the boundaries of the search area. Results displays the synthesis across the four evolutionary stages.

Material and Methods

This review followed a PRISMA-guided systematic process. Because the review was conducted without institutional access to Scopus, Web of Science, ScienceDirect, or EBSCO/Business Source Complete, the search was deliberately restricted to five open-access sources: Google Scholar, CORE, DOAJ, SSRN, and Semantic Scholar. This is stated here as a scope limitation rather than a silent gap, and its consequences are returned to in the Limitations subsection of the Conclusion. The search was further restricted to publications through the end of 2024, so that the review captures a defined evidentiary snapshot rather than an open-ended, continuously moving target.

Identification

Using Boolean combinations of terms created for each of the four evolutionary stages of the review (such as 'customer segmentation', or 'predictive segmentation', or 'hyper-personalization', or 'artificial intelligence' with 'marketing strategy'), 13 anchor-term search batches were conducted across the five target databases. The reason for two of these specific targeted batches was because, after one regarding the Traditional and Emerging coverage stages, a disproportionate amount of runs were focused in the AI-Enabled Hyper-Personalization stage. The search was performed using the title/abstract. In the Identification tracker of the review, there are 71 different records from all batches.

The main anchor strings were: “market segmentation” OR “customer segmentation” OR “segmentation strategy” AND marketing; “predictive segmentation” OR “data-driven segmentation” OR “behavioral segmentation” OR “customer analytics” AND marketing; “hyper-personalization” OR “AI-driven personalization” OR “machine learning personalization” OR “personalized marketing” AND (artificial intelligence OR machine learning); and “research agenda” OR “future research directions” AND AI AND personalization AND marketing. Two additional, targeted batches, that included the search terms “demographic segmentation” OR “psychographic segmentation” AND marketing AND empirical, and voice-assistant- and conversational-commerce-specific strings, were added later, and focused on providing richer data in the Traditional and Emerging stages where the initial 10 batches over-indexed.

Screening and eligibility verification

In accordance with common practice, each record was screened at the title and/or abstract level with an Include/Exclude/Unclear classification, and a reason was logged for every decision. Because many retrieved records could not be reliably confirmed on publication year, venue, or even title from the search-result listing alone, every record not definitively excluded at this stage was subsequently checked against Crossref, the DOI APIs of DOAJ or CORE, or the publication's original web page. This verification step proved substantively important: 22 of the 71 logged records were excluded because their actual, verified publication year post-dated this review's 2024 cut-off, and several of these were a strong topical fit that would likely have been included had verification not caught the date discrepancy. A further 10 records were excluded for other reasons following verification: one for a DOI/metadata mismatch, where the DOI resolved to a different article than the one apparently retrieved; one for a confirmed title mismatch, where the closest verifiable database match shared the same title but proved to be a different article; two undergraduate/master's theses excluded as not peer-reviewed; two records that were too generically titled to be reliably matched to a specific, verifiable source and were therefore excluded rather than assumed to match a plausible-looking candidate; and two records that could not be resolved either way after repeated verification attempts (one confirmed to correspond to a different paper, one linking to a broken or expired page) and which are accordingly not cited anywhere in this review.

A second methodological choice concerned documents that, on inspection, were not primary studies at all but literature reviews, bibliometric analyses, or conceptual research-agenda pieces (including Vlačić et al., 2021; Chandra et al., 2022; Peltier et al., 2024; and Kshetri, 2023). These 10 review-type records were excluded from the main synthesis so that review-of-review material would not be mixed with the primary empirical and conceptual contributions synthesized in Results. Of these 10 records, 9 were independently verified against Crossref, DOAJ, or publisher records with sufficient bibliographic detail and are cited as Introduction-level background sources rather than as included studies. The tenth record could not be matched against any of these sources despite repeated attempts and is therefore not cited anywhere in this review and does not appear in the reference list.

Another quality consideration involves one included study (Kufile et al., 2024), published in a journal whose stated scope is civil engineering rather than AI ethics or marketing, even though its actual content is squarely an AI-ethics/advertising-governance contribution—a mismatch between venue and subject matter that is unusual and worth flagging rather than silently accepting. This record remains in the synthesis because its content, not its venue, determines its relevance, and this venue/content mismatch is noted again in Results at the point where the study is discussed.

As a result of this process, 29 studies were incorporated into the review's synthesis (full record-level detail is retained in the project's Identification, Screening, and Eligibility tracker sheets and is not reproduced here). Of these 29 studies, 2 (Griva et al., 2024; Sidlauskiene et al., 2023) had fully verified bibliographic metadata but no retrievable abstract text in the verification sources used; their findings are therefore reported at the level of verified title, method, and topic only, and are flagged as lower-confidence entries rather than treated as fully reported empirical results.

Data extraction and framework-based synthesis

From each of the 29 studies included the following was extracted: author(s), year, journal/venue, country/setting (if given in the paper), method, framework stage, study type and findings, with “Not stated in paper” used only for studies that actually lacked an indication. The studies were allocated to one of the four framework stages—Traditional/Rule-Based Segmentation, Data-Driven & Predictive Segmentation, AI-Enabled Hyper-Personalization, Emerging/Future Directions—according to the type(s) of segmentation or personalization used by the study, not just the year the study was published (which is, of course, related to the type). The synthesis in Results follows these four stages and is calculated directly from the resulting extraction table.

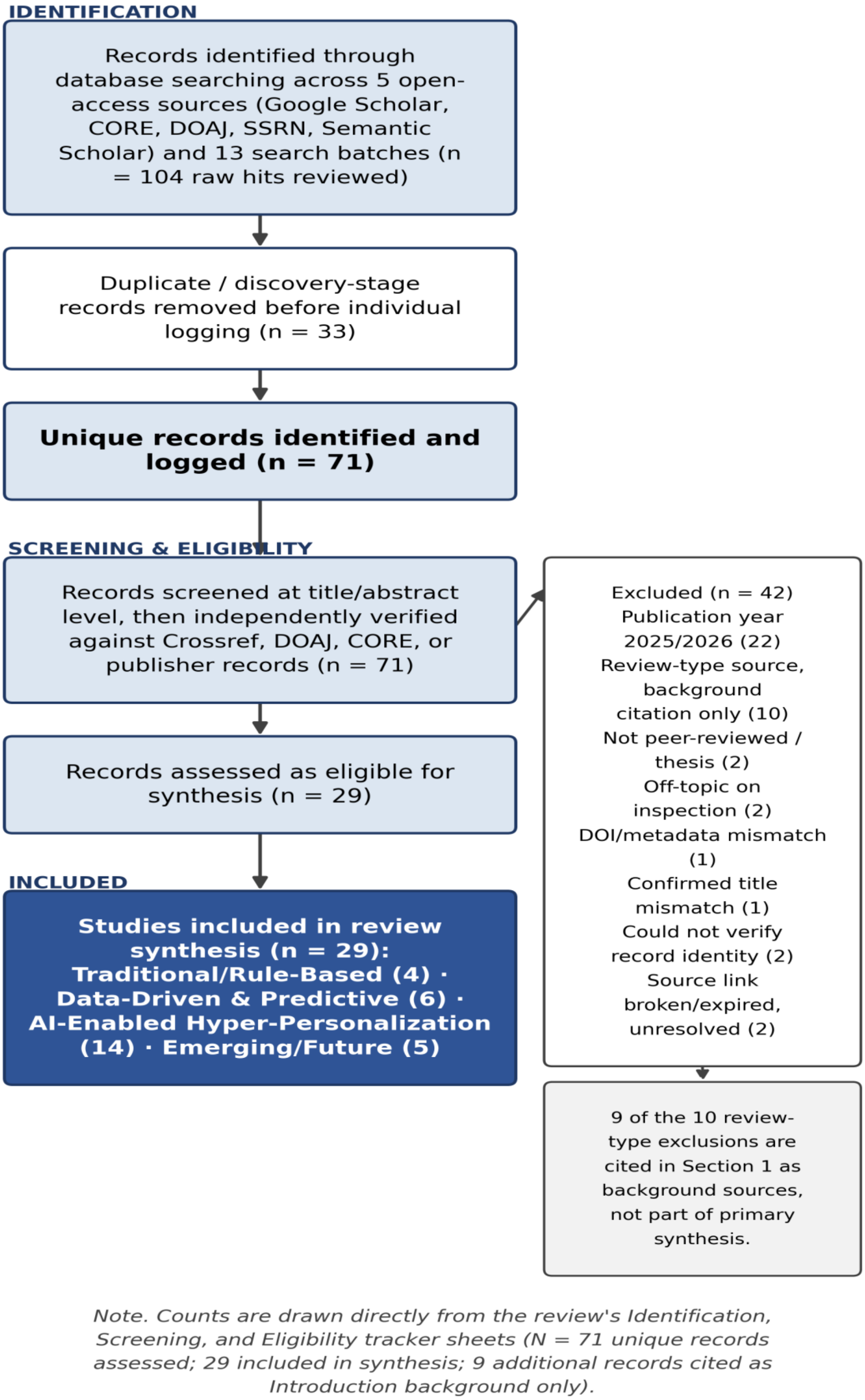

Figure 1. PRISMA-Guided Study Identification and Selection Flow Results

Four studies of Traditional/Rule-Based Segmentation, 6 studies on Data-Driven & Predictive Segmentation, 14 studies on AI-Enabled Hyper-Personalization, and 5 studies on Emerging/Future Directions were included. This distribution is itself a finding: roughly half of the literature included in this review sits at the AI-Enabled stage, even though two additional search rounds were undertaken specifically to add depth to the Traditional and Emerging stages (successfully adding four studies to them). Figure 2 summarizes the segmentation or personalization method characterizing each of the four stages.

Figure 2. Four-Stage Evolutionary Framework of AI-Enabled Marketing Segmentation

Table 1 summarizes all 29 included studies by stage, method, and key contribution, drawn directly from the review's extraction table; the narrative synthesis in the subsections below expands on each entry.

Table 1
Overview of Included Studies (n = 29)

Study	Stage	Method	Key Contribution
Kumar et al. (2012)	Data-Driven & Predictive	Two-phase K-Means (RFM) + demographic clustering + LTV	Separates high/low-value bank segments using RFM-based clustering
Ali (2016)	Traditional / Rule-Based	Survey (n=750), SEM	Segmentation and positioning jointly explain ~60% of satisfaction variance
Jeble et al. (2018)	Data-Driven & Predictive	Conceptual/applied review	Big data enables microsegmentation and real-time predictive analytics
Gajanova et al. (2019)	Traditional / Rule-Based	Hypothesis testing on segmented data	Demographic/psychographic segments differ in brand loyalty
Davenport et al. (2020)	AI-Enabled Hyper-Personalization	Conceptual framework	Foundational AI-in-marketing framework; augment, don't replace, managers
Esfidani et al. (2014)	Traditional / Rule-Based	Interviews + survey (n=669), cluster analysis	Four benefit-based segments in Iranian retail banking
Guha et al. (2021)	Data-Driven & Predictive	ML + A/B testing	A/B testing as 'gold standard' for segment/LTV-based decisions
Kovács et al. (2021)	Data-Driven & Predictive	Two-stage clustering (SOM+hierarchical) + MCA, n=1,542	Distinct investment-pattern clusters in retail banking
Griva et al. (2024)	Data-Driven & Predictive	Two-stage business analytics (title-confirmed only)	Behavioral + geographic segmentation on e-commerce delivery data
Desai (2022)	AI-Enabled Hyper-Personalization	Conceptual framework	ML/AI-integrated segmentation-targeting-positioning framework
Gao & Liu (2023)	AI-Enabled Hyper-Personalization	Conceptual framework	Five-stage customer-journey model of AI personalization
Flavián et al. (2023)	Emerging / Future Directions	Two experiments	Voice-based AI recommendations outperform text reviews
Chuan et al. (2023)	AI-Enabled Hyper-Personalization	Conceptual/critical analysis	Calls for corporate digital responsibility on AI ad surveillance/bias
Acikgoz et al. (2023)	Emerging / Future Directions	Survey (n=491)	Privacy cynicism reduces voice-assistant engagement; trust offsets it
Sidlauskiene et al. (2023)	Emerging / Future Directions	Empirical (title-confirmed only)	AI chatbots in conversational commerce (findings not retrievable)
Tavor et al. (2023)	Traditional / Rule-Based	Mathematical/economic model	Optimal timing of premium-to-discount pricing across segments
Sipos (2024)	AI-Enabled Hyper-Personalization	Comparative analysis	AI hyper-personalization improves engagement/retention/conversion
Guendouz (2024)	AI-Enabled Hyper-Personalization	Theoretical/conceptual	Frames hyper-personalization as an Industry 4.0-to-5.0 shift
Preciado-Ortiz et al. (2024)	AI-Enabled Hyper-Personalization	Conceptual/literature-based	Generative AI aids UX/loyalty; flags missing ROI standards

Ainapur et al. (2024)	AI-Enabled Hyper-Personalization	Case study (Amazon, Netflix)	AI automates/optimizes/personalizes marketing functions
Kotha (2024)	AI-Enabled Hyper-Personalization	Empirical/applied	Reports +25% revenue, +15% retention from AI personalization
Gungunawat et al. (2024)	AI-Enabled Hyper-Personalization	Conceptual/applied	AI analytics/ML craft focused strategies; flags bias/privacy
Babadoğan (2024)	AI-Enabled Hyper-Personalization	Conceptual/applied	Real-time segmentation; 'filter bubble' risk identified
Liu (2024)	AI-Enabled Hyper-Personalization	Practitioner/insight piece	Personalization drives engagement; over-personalization risk
Para (2024)	AI-Enabled Hyper-Personalization	Computational linguistics	Linguistic-style-based adaptive personalization raises engagement
Kufile et al. (2024)	AI-Enabled Hyper-Personalization	Conceptual framework	Fairness/accountability/transparency/explainability framework
Li & Lee (2024)	Data-Driven & Predictive	SVM + clustering	6.82% error rate, 91.28% recall, profit within 2.53% of actual
Pandiyan & Pandian (2024)	Emerging / Future Directions	Trend overview	Surveys 2024 trends: AI, video, voice search, privacy, social commerce
Muminov (2024)	Emerging / Future Directions	Synthesis of sources	AI personalization evolving toward hyper-personalized experience

Traditional / Rule-Based Segmentation (n = 4)

The smallest and most homogeneously methodologically stage consists of four studies, none of which make use of AI or machine-learning approaches. Ali (2016) conducted 750 survey responses from customers in 100 restaurants and applied the method of structural equation modeling that shows that market segmentation has a significant effect on the positioning strategy, and segmentation and positioning and customer value perception contribute to the prediction of customer satisfaction with values of R^2 around 60%. Gajanova et al. (2019) examined whether customer segments based on demographic and psychographic aspects differ in the levels of brand loyalty they measure and concluded that some segments indicated statistically higher brand loyalty than others. Entitled 'Retail banking market segmentation based on the expected benefits of Bank Mellat customers', Esfidani et al.'s (2014) study used benefit-based segmentation for retail banking in Iran and applied exploratory interviews and expert review to reduce 166 candidate customer benefits to 50, followed by a cluster analysis on 669 respondents to generate four segments that differ mainly on trust, convenience, ease of use, and technology. Tavor et al. (2023), by contrast, approached the issue differently: they modeled the optimal strategy for when firms should shift a newly introduced product from premium to discounted pricing for each customer segment, and showed an increase in customer revenues and profit as a result of segmentation, as a price-sensitive segment purchases less under uniform pricing but a loyal segment purchases more under targeted pricing.

In sum, these four studies span publication years from 2014 to 2023 but share the common characteristic that they use statistical hypothesis-testing or closed-form economic modeling rather than any algorithmic learning method as the basis for segmentation; even the most recent, Tavor et al. (2023), is a mathematical pricing model rather than a machine-learning system. This stage's small size relative to the other three is probably driven as much by this review's AI- and personalization-oriented search terminology as by any actual scarcity of traditional-segmentation scholarship, and is addressed as a limitation below.

Data-Driven & Predictive Segmentation (n = 6)

This stage shows a largely linear methodological evolution from 2012 to 2024. Kumar et al. (2012) present one of the review's earliest papers, a two-phase clustering method that first clusters bank customers on recency, frequency, and monetary (RFM) metrics and then applies demographic sub-clustering and lifetime-value (LTV) analysis to distinguish high-value from low-value customer segments. Jeble et al. (2018) raised concerns about data privacy, systems integration, and governance that persisted throughout the later AI-Enabled literature, framed around micro-segmentation, real-time data updating, and predictive analytics. Guha et al. (2021) describe using machine-learning approaches together with A/B testing to identify high-value customer segments and estimate their lifetime value, positioning A/B testing as a 'gold standard' for evidence-based segmentation decisions. Using 1,542 retail-banking survey responses, Kovács et al. (2021) applied a two-stage clustering method—first a Kohonen self-organizing map, then hierarchical clustering and multiple correspondence analysis—to cluster categorical and numerical data together, defining distinct groups of investors, risk takers, and advice recipients. Li and Lee (2024) present a segmentation model based on support vector machines (SVMs) and clustering that achieved a mean error rate of 6.82% and mean recall of 91.28% across 50 iterations, with predicted profits within 2.53% of actual. No abstract text for Griva et al. (2024) could be retrieved from the verification sources used, so its detailed quantitative findings are not presented here; only its verified method (behavioral and geographic segmentation) and dataset (real e-commerce delivery data) are reported.

As a group, these six studies show a progression in segmentation methodology from RFM-plus-demographic clustering, through the use of big data in segmentation, to machine-learning clustering combined with formal experimentation during 2021–2024, with a growing emphasis on real behavioral or transactional data over survey-collected attributes.

AI-Enabled Hyper-Personalization (n = 14)

This is the largest stage in the review, and its name most directly matches the evolutionary narrative the review's title describes. Two studies provide foundational or theoretical grounding rather than empirical results: Davenport et al. (2020) is the most frequently cited study in this stage, offering general background on how AI functions within marketing, while Desai (2022) grounds hyper-personalization theory specifically in the application of machine learning and AI to the segmentation-targeting-positioning (STP) process. Guendouz (2024) extends this theoretical grounding by framing the shift as part of a broader Industry 4.0-to-5.0 transformation, driven by machine learning, natural language processing, and generative AI within customer relationship management (CRM).

Several 2024 studies report quantified engagement or business outcomes attributed to AI-driven personalization. Kotha (2024) reports revenue increases of up to 25% and retention improvements of 15% associated with AI-driven hyper-personalization, predictive analytics, and conversational AI used for lead qualification and engagement. Sipos (2024) and Preciado-Ortiz et al. (2024) both report improvements in engagement, satisfaction, retention, and conversion from AI-driven and generative-AI-driven personalization respectively, though Preciado-Ortiz et al. (2024) explicitly note the absence of standardized metrics for measuring the return on investment of generative-AI marketing—a measurement gap discussed further below. Ainapur et al. (2024) illustrate these effects through the frequently cited cases of Amazon's recommendation system and Netflix's content-personalization approach. Babadoğan (2024) and Gungunawat et al. (2024) both discuss AI-enabled real-time segmentation and adaptive personalization systems, and Liu (2024) situates personalization within broader digital-marketing engagement outcomes, though this source is a practitioner-oriented insight publication rather than a peer-reviewed research journal and its claims are weighted accordingly in this synthesis. Para (2024) narrows the focus considerably, proposing that analyzing users' linguistic style (formality, emotional tone, level of detail) can drive adaptive content personalization, reporting gains in brand loyalty and click-through rate; this is a more technical, computational-linguistics contribution than the review's typical marketing-strategy focus, and its journal's standing was not independently verified.

Two studies focus specifically on ethics and governance. Kufile et al. (2024) propose a conceptual framework built around fairness, accountability, transparency, and explainability for AI personalization in programmatic advertising specifically—noting again, as disclosed in Methodology, that this study's publishing venue does not match its subject matter. Chuan et al. (2023) argue more broadly for corporate digital responsibility in AI advertising, connecting hyper-personalization to consumer surveillance and algorithmic bias and calling for greater AI literacy and industry accountability. Gao and Liu (2023) offer one of the stage's few process-level (rather than outcome-level) contributions, developing a five-stage customer-journey framework in which AI-enabled personalization manifests as profiling, navigation, nudges, and retention.

Across these fourteen studies, three patterns emerge. First, AI-driven personalization is explicitly linked to improved engagement, retention, or conversion outcomes. Second, this comes with recurring—and largely unaddressed—concerns about data privacy and algorithmic bias. Third, several of the more recent 2024 studies report that a positive outcome was achieved while simultaneously acknowledging that no standardized metric exists for measuring or attributing that effectiveness—that is, the gain is reported, but the yardstick for measuring it is explicitly described as unsettled.

Emerging / Future Directions (n = 5)

This stage is the review's most technologically heterogeneous, and its five studies do not form a single coherent research stream. Pandiyan and Pandian (2024) provide a broad 2024 trend overview spanning AI-driven strategies, video content, voice-search optimization, privacy-focused approaches, and social commerce, recommending that marketers pursue personalization and data-privacy protection jointly rather than treating them as competing priorities; this contribution offers breadth across several emerging developments rather than depth on any single one. Muminov (2024) argues, synthesizing academic and industry sources, that AI-driven personalization is evolving beyond conventional segmentation toward increasingly hyper-personalized experiences via predictive analytics and conversational AI, while still flagging privacy and algorithmic-bias concerns as unresolved.

The following two studies focus more specifically on voice-based AI. Flavián et al. (2023) present two experimental studies showing that an AI voice recommender perceived as credible and useful, and delivered in a male voice (moderator), can influence consumer behaviour toward a searched-for product more than in-text online reviews do. Acikgoz et al. (2023) surveyed 491 users and found that privacy cynicism negatively affects AI voice-assistant use, while trust, perceived usefulness, and ease of use each have a positive influence, with these latter three effects moderated by habit. Sidlauskiene et al. (2023) is included on the strength of its confirmed topic and method alone—no abstract text was retrievable for this study—but it is nonetheless an empirical study of AI-based chatbots in conversational commerce and their effect on product and price perception.

This remains one of the two thinnest stages in the review, alongside Traditional/Rule-Based Segmentation, a point discussed further as a limitation below despite a dedicated search round aimed at adding depth to this stage.

Cross-Cutting Patterns

Several cross-cutting patterns emerge from reading the four stages together rather than in isolation. First, concerns about data privacy, algorithmic bias, or the ethics of AI-driven personalization are not confined to any single stage or study: they appear explicitly in at least nine of the nineteen studies classified under the AI-Enabled Hyper-Personalization and Emerging/Future Directions stages combined (Sipos, 2024; Preciado-Ortiz et al., 2024; Gungunawat et al., 2024; Babadoğan, 2024; Chuan et al., 2023; Kufile et al., 2024; Para, 2024; Acikgoz et al., 2023; Muminov, 2024), and the concern is not limited to those two stages either—Jeble et al. (2018), classified under Data-Driven & Predictive Segmentation, raises the same data-privacy and governance issues nearly a decade earlier in the review's timeline. This is a directly countable pattern in the extraction table rather than an inferred one, and it suggests that ethical and privacy concerns are treated in this literature as a persistent, cross-stage feature of the segmentation-to-personalization progression rather than as an occasional caveat confined to the most recent AI-enabled work.

Second, none of the later cited studies explicitly rebut Davenport et al.'s (2020) claim that AI works best when supplementing, rather than substituting for, a human marketing manager, but neither do they often return to this question, since many of the studies simply report results from personalizing or ethical issues. This is offered here as a more inferential comment on the structure of the literature as a whole and not as a finding reported by any individual included study.

Third, there is a measurement impasse in this literature. Most included studies report their own bespoke metrics—for example, Li & Lee (2024) report a 6.82% error rate and 91.28% recall for their segmentation model, while Kotha (2024) reports a 25% revenue increase and 15% retention improvement—but a few of the 2024 studies explicitly state that no standardized return-on-investment or effectiveness metric yet exists for AI-driven or generative-AI-driven personalization (Preciado-Ortiz et al., 2024). This acknowledged gap, combined with each author reporting a different bespoke metric, does not mean the individual measurements are unreliable; it means the field's measurement methods have not yet been harmonized and the reported figures are not directly comparable across studies.

Fourth, the evolutionary arc named in this review's title is visible in the included evidence but is not evenly populated along its length: studies using purely demographic, psychographic, or benefit-based segmentation cluster in 2014–2023 (Traditional stage), studies using clustering, RFM, or predictive-analytics methods span 2012–2024 relatively continuously (Data-Driven stage), and studies explicitly framing their contribution around AI-enabled or generative-AI-enabled hyper-personalization concentrate almost entirely in 2022–2024 (AI-Enabled stage). This pattern is consistent with a genuine acceleration of AI-enabled marketing scholarship in the years immediately preceding this review's 2024 cutoff, but should also be read partly as an artifact of a search strategy that used AI- and personalization-specific anchor terms; a search designed instead to exhaustively cover the Traditional and Data-Driven stages, drawing on subscription-access marketing journals this review could not reach, might well surface a larger and older body of traditional-segmentation scholarship than is represented here.

Fifth, the included literature skews conceptual and practical rather than empirical. Of the 29 studies examined, 12 are empirical in the traditional sense: an experiment (Flavián et al., 2023); a survey (Acikgoz et al., 2023; Ali, 2016; Esfidani et al., 2014); or a quantitative applied model or clustering method tested against real data (Kumar et al., 2012; Guha et al., 2021; Kovács et al., 2021; Griva et al., 2024; Sidlauskiene et al., 2023; Gajanova et al., 2019; Kotha, 2024; Li & Lee, 2024). The remaining 17 are conceptual frameworks, trend syntheses, case illustrations, or practitioner-oriented pieces. This is not a criticism of those 17 studies, many of which are explicit about the conceptual or applied nature of the model they present—but it does mean that performance figures such as Kotha's (2024) reported 25% revenue uplift should be read as a single reported result rather than as a finding replicated across the controlled conditions of empirical research. A reader treating this review as evidence that AI-enabled personalization 'works' should weight the 12-study empirical subset of Table 1 more heavily than the 17-study conceptual majority, rather than treating the two as equivalent-strength evidence.

Sixth, on industry and geographic context: relatively few of the 29 included studies state an explicit country or industry setting. Ali (2016) is explicit about its setting (Bandung City restaurants), and Esfidani et al. (2014) explicitly names its country context (Iran); by contrast, Sidlauskiene et al.'s (2023) setting could not be confirmed beyond its title. Notably, three of the included studies—Esfidani et al. (2014) in the Traditional stage, and Kovács et al. (2021) and Kumar et al. (2012) in the Data-Driven stage—are all set in retail banking, suggesting that retail banking may be a particularly attractive setting for segmentation research generally, rather than one specifically driving adoption of AI tools. Beyond this cluster, most included studies—particularly those in the AI-Enabled stage—describe their contribution at a fairly high level of abstraction, without specifying the sector or market in which it was deployed; this review does not assume the evolutionary pattern it describes is confined only to the few sectors (e.g., e-commerce, banking) where such detail happens to be reported more often.

Seventh, the four-stage framing itself carries a theoretical and a practical implication worth stating directly rather than leaving implicit. Theoretically, organizing the included literature by evolutionary stage rather than by AI capability level (Davenport et al., 2020) or marketing task makes visible a structural claim that runs through the AI-Enabled stage specifically: that AI-enabled hyper-personalization is presented in this literature not merely as data-driven segmentation performed with newer tools, but as a shift in the basic unit of marketing decision-making, from the segment to the individual, consistent with Desai's (2022) hyper-personalization framework and Guendouz's (2024) framing of that shift as comparable in scale to a broader Industry-4.0-to-5.0 transition. This distinguishes the evolutionary account offered here from capability- or task-organized frameworks without displacing them; the two ways of organizing the same literature are complementary rather than competing. Practically, the coexistence documented in the third pattern above—reported effectiveness gains (Kotha, 2024; Li & Lee, 2024) alongside an explicitly acknowledged absence of standardized measurement (Preciado-Ortiz et al., 2024)—suggests that practitioners evaluating AI-enabled personalization investments should treat the individual performance figures reported in this literature as illustrative of what has been claimed rather than as benchmarks known to transfer across organizational contexts. And because privacy and algorithmic-bias concerns recur not only across the AI-Enabled and Emerging stages but as early as the Data-Driven stage (Jeble et al., 2018), this review's evidence suggests governance and ethical-design considerations are better treated as a design input from the outset of an AI-enabled personalization strategy than as a compliance step added once a system is already built.

Conclusion

Returning to the four research questions that guided this review: the shift from rule-based practice grounded in demographic, psychographic, and benefit segmentation (RQ1), to a data-driven approach using clustering, RFM, and predictive analytics (RQ2), and on to hyper-personalization that integrates machine learning into segmentation, targeting, and positioning (STP) (RQ3), is the central evolutionary step this review traces. Machine-learning tools and predictive analytics generally, and conversational AI and voice-based agents specifically in the most recent literature, are most closely associated with this latter transition. The marketing outcomes associated with this evolution, relative to earlier segmentation strategies, are consistently reported increases in customer engagement, retention, and conversion (RQ3), alongside persistent and unresolved concerns about data privacy, algorithmic bias, and inconsistency in how AI-driven segmentation's effectiveness is measured. The most recent and still-developing strands of this literature suggest that conversational commerce and voice-based AI interaction are the directions most likely to shape where this evolution goes next.

Because this review's search-term scope and date range limit how much of the literature it could capture, its evolutionary account is best read as accurate but unevenly evidenced—a picture that a more generously resourced investigation, one able to draw on subscription marketing databases and a wider time window and search-term set, is well positioned to extend.

Limitations

All evidence for this review was compiled from open-access sources (Google Scholar, CORE, DOAJ, SSRN, and Semantic Scholar) rather than from subscription databases such as Scopus, Web of Science, ScienceDirect, and EBSCO/Business Source Complete. This will likely have had the largest impact on the Traditional and Data-Driven stages: relevant scholarship in these areas tends to be older and more often accessible only by subscription in well-established marketing journals, compared with the AI-marketing literature, which is concentrated in the last five years and more frequently open access.

Relatively few studies were ultimately included given the breadth of the topic, even though the review's included evidence spans a wide window—2012 through 2024—rather than a narrow one; the small final count instead reflects the strictness of the verification process described in Methodology, not a short search timeframe. Several additional candidate studies were identified during searching but filtered out individually for insufficient topical fit, including papers on 'hyper-personality versus marketing leadership', 'AI-driven culturally aware customer segmentation and targeting', 'generative AI in advertising agencies', and 'generative AI in visual marketing content production'. This review is therefore best read as a snapshot of the evidence up to its 2024 cut-off, immediately before what the excluded candidates' framing suggests may be a considerably larger subsequent expansion of AI-marketing scholarship, and should not be read as reflecting the state of that scholarship beyond the delimited timeframe.

Ten of the in-scope, within-date-range records were themselves literature reviews, bibliometric analyses, or research-agenda items, and were therefore intentionally excluded from primary synthesis (see Methodology). Of these ten, nine are cited as Introduction-level background sources; the tenth is not cited anywhere in this review, despite repeated verification attempts, because it could not be confirmed against Crossref, DOAJ, or publisher metadata. A review with a broader scope—one that formally integrated primary studies and existing reviews rather than treating the latter as background only—could plausibly reach different conclusions, particularly regarding the size and boundaries of the AI-Enabled stage.

Two records with generically similar titles, for which repeated attempts to identify a reliable tie-in to an actual, verifiable data source were unsuccessful, were excluded on the basis of a plausible-looking but unverifiable match rather than assumed inclusion. For two studies (Griva et al., 2024, and Sidlauskiene et al., 2023), bibliographic metadata were fully confirmed, but because no abstract text could be retrieved, these should not be read as verified empirical findings but only as confirmed in method and topic, as reported in Results. One included study (Kufile et al., 2024) was published in a journal whose stated scope does not match the study's actual subject matter; this is noted here rather than resolved, and readers should weigh it accordingly.

Finally, notwithstanding two search rounds focused on adding depth to underrepresented stages, Traditional/Rule-Based Segmentation (n = 4) and Emerging/Future Directions (n = 5) remain this review's smallest stages, at roughly a third of the size of AI-Enabled Hyper-Personalization (n = 14). The conclusions reached about these two stages in Results are correspondingly provisional and sensitive to the inclusion of a few additional studies, whereas the conclusions reached about the Data-Driven or AI-Enabled stages are less sensitive in this way.

Recommendations

This review's findings point to several concrete directions for future research and for marketing practice. First, the persistent absence of standardized effectiveness metrics identified above—where studies as recent as 2024 report AI-driven personalization outcomes using incompatible, self-defined measures—means that future empirical work should adopt or propose shared benchmarks for measuring the return on investment and effectiveness of AI-enabled personalization, so that findings such as Kotha's (2024) reported revenue gains or Li and Lee's (2024) reported error and recall rates can eventually be compared directly across studies rather than read in isolation.

Second, because concerns about data privacy and algorithmic bias recur across every stage of this literature from Jeble et al. (2018) onward rather than being confined to the most recent AI-enabled work, organizations adopting AI-driven personalization should treat privacy and algorithmic-fairness governance as a design requirement built in from the outset of a personalization initiative, rather than as a compliance step addressed only after a system is deployed.

Third, given this review's evidentiary imbalance—the Traditional/Rule-Based (n = 4) and Emerging/Future Directions (n = 5) stages together account for fewer included studies than the AI-Enabled stage alone (n = 14), an imbalance this review attributes in part to its restriction to open-access sources—future systematic reviews of this literature should, where institutional access allows, extend the search to subscription-access databases such as Scopus, Web of Science, and EBSCO/Business Source Complete, particularly to capture older traditional-segmentation scholarship and emerging voice- and conversational-commerce research that this review's open-access-only search strategy may under-represent.

Fourth, because 17 of the 29 included studies are conceptual, trend-synthesis, or practitioner-oriented contributions rather than controlled empirical studies, researchers designing new studies in this area should prioritize empirical designs—experiments, surveys, or applied models tested against real behavioral or transactional data—that can validate or qualify the effectiveness claims that currently rest on a comparatively small empirical base of 12 studies.

Finally, practitioners evaluating vendor or in-house claims about AI-enabled personalization should treat single-study performance figures reported in this literature as illustrative rather than as benchmarks proven to transfer across organizational contexts, given both the field's unresolved measurement-standardization gap and the predominance of conceptual over empirical evidence documented in this review.

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