INTERNATIONAL JOURNAL OF BUSINESS AND ECONOMICS INSIGHTS

Volume: 3; **Issue:** 1
Pages: 68– 96
Accepted: 13 March 2023
Published: 30 March 2023

A SYSTEMATIC REVIEW OF PREDICTIVE ANALYTICS IN MARKETING DECISION-MAKING EXPLORING AI-DRIVEN CONSUMER SEGMENTATION AND AB TESTING

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Doi: 10.63125/2hvfh110

This work was peer-reviewed under the editorial responsibility of the IJEI, 2023

Abstract

This systematic review examines how predictive analytics supports marketing decision-making by synthesizing research on AI-driven consumer segmentation and A/B testing strategies as complementary components of evidence-based marketing systems. Using a PRISMA-guided screening and selection workflow, the review analyzed a total of 57 papers that met predefined eligibility criteria focused on marketing-relevant predictive modeling, segmentation methods used for decision support, and experimentation designs applied to validate marketing interventions and personalization policies. Findings indicate that predictive analytics is most often operationalized as an end-to-end decision pipeline in which diverse data ecosystems – spanning first-party CRM and transaction histories, digital behavioral traces, campaign exposure logs, contextual signals, and content-based attributes are transformed through feature engineering into model-ready representations that drive targeting, retention, personalization, and pricing or promotion decisions. The reviewed studies show that segmentation has expanded beyond traditional strategic planning roles to include tactical campaign governance, analytical feature construction, and high-granularity personalization through clustering, probabilistic membership models, representation learning, and deep latent-space approaches, with interpretability and segment stability repeatedly emphasized as prerequisites for operational use. The experimentation literature positions A/B testing as the central causal validation mechanism for selecting among creative variants, interface designs, targeting rules, and algorithmic policies, while also highlighting the importance of metric governance, attribution windows, statistical power, multiple-comparison control, and operational safeguards such as ramping, logging, and auditability. Across the evidence base, the strongest contributions link prediction, segmentation, and experimentation into integrated decision cycles where model outputs prioritize audiences, segment's structure heterogeneity for analysis and governance, tests estimate incremental effects, and results update thresholds and rollout rules under real constraints. Overall, this review consolidates a fragmented literature into a coherent synthesis of methods, evaluation standards, and operational patterns that characterize how predictive analytics, AI segmentation, and A/B testing jointly function as a scalable decision architecture in contemporary marketing environments.

Keywords

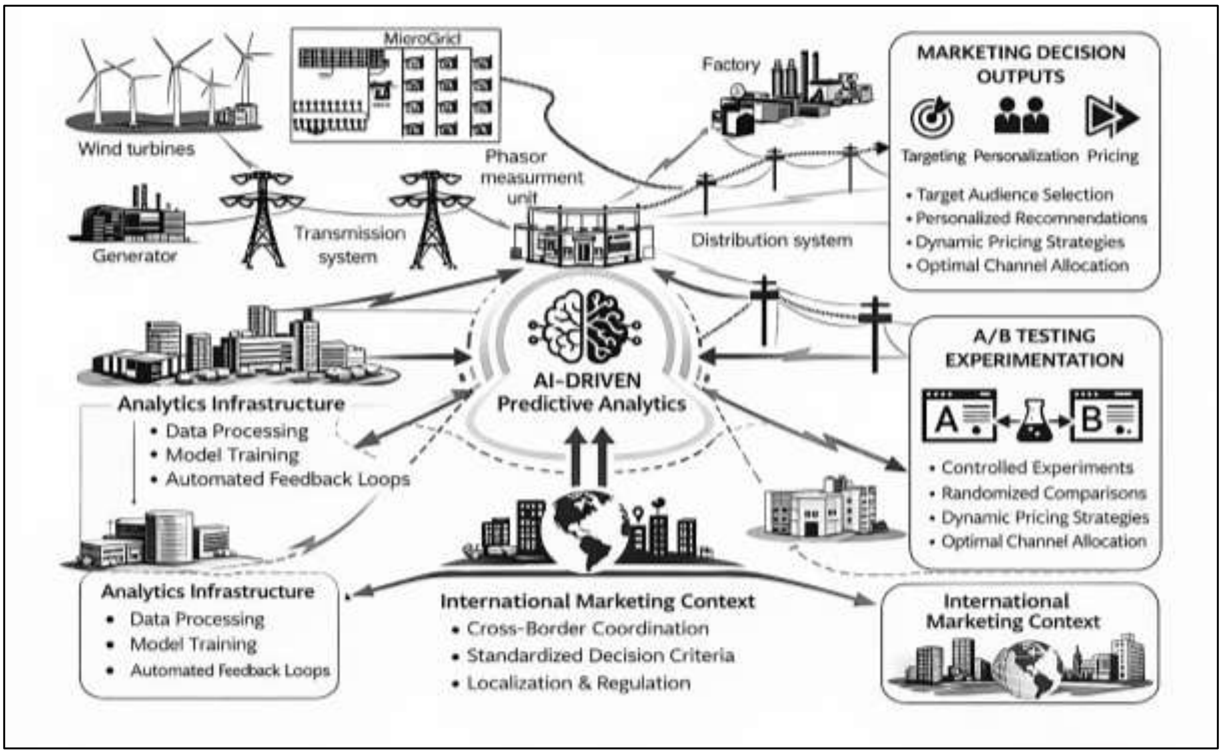
Predictive analytics; AI segmentation; A/B testing; Marketing decisions; Experimentation.

INTRODUCTION

Predictive analytics in marketing decision-making refers to the systematic application of statistical modeling, machine learning algorithms, and computational reasoning to analyze historical and real-time data in order to estimate the likelihood of future consumer behaviors and market responses (Sarker, 2021). Within marketing contexts, predictive analytics is commonly operationalized through probabilistic scoring, classification, and pattern recognition techniques that support decisions related to targeting, personalization, pricing, promotion design, and channel allocation. Unlike descriptive analytics, which focuses on summarizing past outcomes, predictive analytics emphasizes forward-looking estimation, enabling marketers to anticipate consumer actions before they occur. This distinction is critical because marketing decisions are inherently made under conditions of uncertainty, where outcomes depend on consumer preferences, competitive dynamics, and contextual signals that are not fully observable at the time of decision (Bradlow et al., 2017). Artificial intelligence functions as an enabling layer within predictive analytics by providing automated learning mechanisms capable of extracting complex relationships from large-scale, high-dimensional data. AI-driven marketing analytics integrates supervised learning for outcome prediction, unsupervised learning for structure discovery, and algorithmic optimization for decision support. Consumer segmentation and A/B testing represent two foundational mechanisms through which predictive analytics is translated into actionable marketing decisions. Segmentation structures consumer heterogeneity into analytically meaningful groups, while A/B testing enables empirical evaluation of alternative marketing actions through controlled experimentation. Together, these mechanisms form a decision infrastructure that links data to action. At an international level, predictive analytics has become a central organizing principle for digital marketing operations across global firms, platforms, and marketplaces. Organizations operating across borders rely on predictive models to standardize decision criteria, allocate resources efficiently, and coordinate marketing activities across diverse consumer populations (Soni & Sharma, 2021). The definitional clarity of predictive analytics is therefore essential for understanding its role not merely as a technical tool, but as a decision-making paradigm that shapes how marketing knowledge is generated, validated, and operationalized within global economic systems.

The international significance of predictive analytics in marketing decision-making arises from the globalization of digital commerce, the platformization of consumer interactions, and the increasing reliance on data-driven coordination across markets. As firms expand operations across national boundaries, marketing decision-making becomes more complex due to variation in consumer behavior, media environments, regulatory constraints, and cultural norms (Miklosik et al., 2019). Predictive analytics provides a unifying analytical language that converts diverse consumer signals into standardized metrics such as probabilities, scores, and expected values that can be compared, aggregated, and acted upon across regions. In multinational organizations, predictive models are frequently embedded into centralized marketing systems that support campaign planning, customer relationship management, and performance monitoring at scale. These systems enable decision-makers to evaluate marketing actions using consistent criteria, even when underlying data sources differ across markets. Predictive analytics also supports coordination between global headquarters and local market units by translating localized consumer data into comparable indicators that inform strategic oversight (Grover & Kar, 2017). In emerging economies, predictive analytics enables firms to compensate for limited traditional market research by leveraging digital traces such as mobile interactions, e-commerce behavior, and platform engagement. In mature markets, analytics supports fine-grained personalization and optimization within saturated competitive environments. Across both contexts, AI-driven predictive systems increasingly shape how marketing decisions are justified, audited, and repeated. Consumer segmentation and A/B testing play particularly important roles in this international landscape because they structure how heterogeneity is recognized and how evidence is generated. Segmentation defines which consumer differences are considered actionable, while experimentation determines which marketing actions are validated through empirical comparison (Chong et al., 2017). The widespread adoption of these practices across global firms underscores their significance as institutionalized components of modern marketing decision systems rather than isolated analytical techniques.

Figure 1: AI-Driven Predictive Marketing Framework



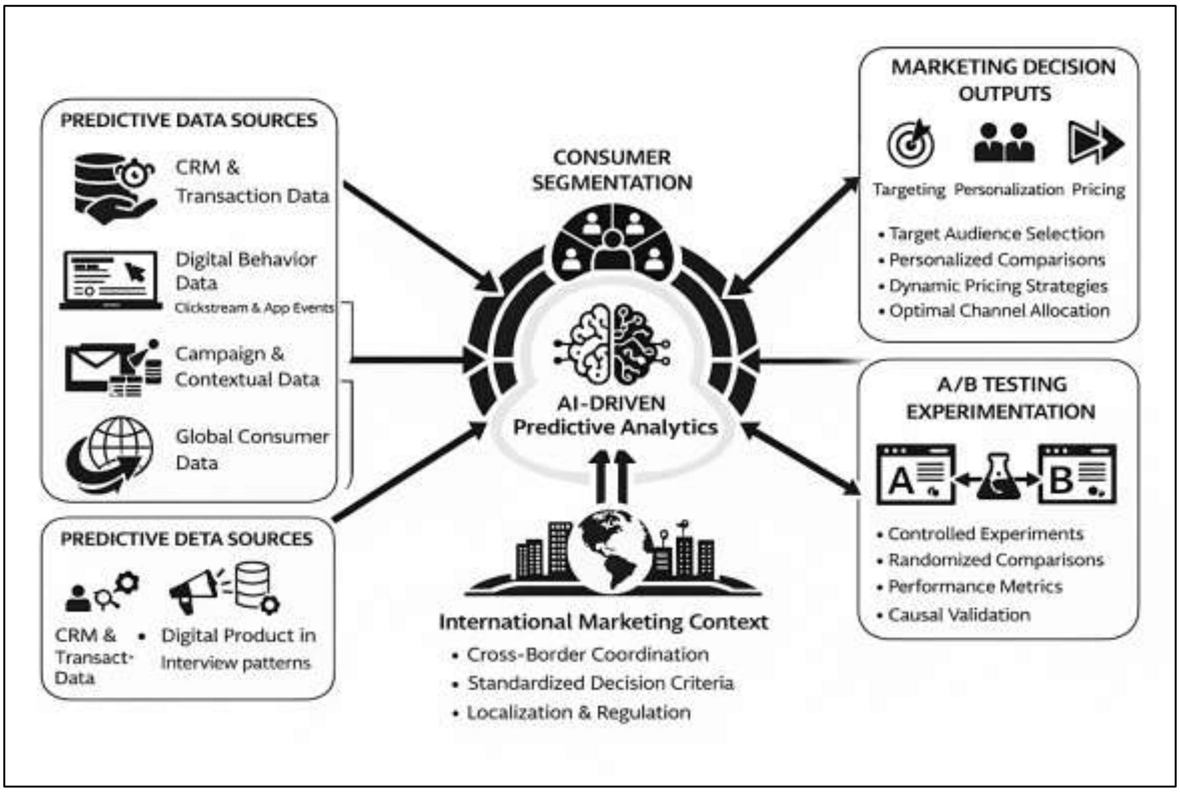
Consumer segmentation is a foundational concept in marketing that refers to the systematic grouping of consumers into distinct categories based on shared characteristics, behaviors, or response patterns. The primary purpose of segmentation is to reduce market complexity by identifying subsets of consumers that can be targeted with differentiated marketing strategies (Nosratabadi et al., 2020). Traditional segmentation approaches have relied on demographic, geographic, psychographic, and behavioral variables to construct segments that are meaningful for planning and positioning decisions. In analytical terms, segmentation represents an abstraction process that transforms continuous and multidimensional consumer heterogeneity into discrete structures that can be operationalized within marketing systems. Predictive analytics expands the scope of segmentation by enabling the use of large-scale behavioral data, transactional histories, and digital interaction traces to define segments empirically rather than intuitively (Arfan et al., 2021; Jahid, 2021; Syam & Sharma, 2018). Algorithmic segmentation methods apply clustering, mixture modeling, and pattern discovery techniques to identify latent structures within data, allowing segments to emerge from observed behavior rather than predefined categories. Within marketing decision-making, segments may function as targets for campaigns, inputs for predictive models, or organizing units for performance analysis. The quality of a segmentation scheme is therefore evaluated not only by statistical criteria but also by its usefulness for decision execution, interpretability by managers, and stability over time. In global marketing contexts, segmentation acquires additional complexity because consumer similarities and differences are shaped by cultural, economic, and institutional factors that vary across regions. Predictive analytics enables firms to construct segmentation frameworks that are locally responsive while remaining analytically consistent across markets (Appelbaum et al., 2017; Akbar & Farzana, 2021; Reza et al., 2021). As a result, consumer segmentation operates as both a cognitive tool for understanding markets and a technical mechanism for embedding consumer heterogeneity into predictive marketing systems.

AI-driven consumer segmentation extends traditional segmentation approaches by incorporating advanced learning architectures capable of processing complex, high-dimensional, and unstructured data. In digital marketing environments, consumer data often includes clickstreams, browsing sequences, textual interactions, images, and temporal engagement patterns that exceed the capacity of conventional analytical techniques (França et al., 2021). AI-based segmentation systems use representation learning to transform raw data into latent features that capture similarity relationships among consumers. These latent representations can then be clustered or classified to produce segments that reflect underlying behavioral structures rather than surface-level attributes. AI-driven segmentation is frequently integrated into automated marketing pipelines where segments are dynamically updated as new data becomes available. This dynamic nature alters the role of segmentation in decision-making by shifting it from a static planning artifact to a continuously learned component of operational systems. In addition to performance considerations, AI-driven segmentation introduces interpretability challenges because complex models may obscure the features that define segment boundaries. Marketing decision-making requires segments to be explainable enough to guide creative strategy, messaging, and resource allocation (Liang et al., 2020; Zobayer, 2021a, 2021b). Consequently, segmentation systems increasingly incorporate explainability mechanisms that translate algorithmic outputs into human-interpretable descriptors. In international marketing contexts, AI-driven segmentation allows firms to adapt segmentation logic to local data availability while maintaining methodological coherence across markets. These systems support scalable personalization by enabling marketing actions to be tailored at granular levels without manual intervention. AI-driven segmentation therefore functions as a critical interface between predictive analytics and actionable marketing decisions, shaping how consumer diversity is represented, managed, and acted upon within global marketing infrastructures (Gutierrez-Franco et al., 2021; Ariful & Ara, 2022).

A/B testing represents a core methodological framework for validating marketing decisions through controlled experimentation. In its simplest form, A/B testing involves randomly assigning consumers to alternative versions of a marketing element and comparing observed outcomes to estimate the effect of each variant (Arman & Kamrul, 2022; Ullah et al., 2019). This experimental logic provides a mechanism for isolating causal effects by ensuring that observed differences in outcomes can be attributed to the tested intervention rather than confounding factors. In marketing decision-making, A/B testing is used to evaluate a wide range of actions, including creative designs, pricing structures, promotional messages, website layouts, and targeting rules. Predictive analytics and AI enhance experimentation by enabling scalable test design, automated metric tracking, and rapid analysis of results. In digital marketing environments, experimentation infrastructure is often embedded directly into platforms, allowing continuous testing across multiple dimensions simultaneously (Lepri et al., 2017; Abdur & Haider, 2022). The role of A/B testing extends beyond evaluation to governance, as experimental results frequently serve as formal justification for deploying or discontinuing marketing actions. At an international level, experimentation enables firms to assess whether marketing strategies perform consistently across markets or require localization. A/B testing also interacts with segmentation by enabling differential effects to be measured across consumer groups, thereby informing targeted decision rules. The integration of experimentation into marketing operations reflects a broader shift toward evidence-based decision-making, where actions are validated through systematic comparison rather than intuition or precedent (Huang & Rust, 2021; Mushfequr & Praveen, 2022).

Predictive analytics, consumer segmentation, and A/B testing are increasingly integrated within unified marketing decision systems that combine prediction, targeting, and causal validation. Predictive models estimate the likelihood of consumer responses, segmentation structures organize heterogeneity, and experiments validate the incremental impact of actions (Hair & Sarstedt, 2021; Mortuza & Rauf, 2022). This integration supports decision rules that focus on selecting the most effective action for each consumer or segment based on estimated outcomes. One prominent integration approach involves modeling incremental effects, where the objective is not merely to predict behavior but to estimate how behavior changes in response to a specific marketing intervention. Such approaches align predictive analytics with experimental logic by embedding causal assumptions into model design. In practice, segmentation may be used to define experimental strata, reduce variance, or interpret heterogeneous treatment effects (Iqbal et al., 2020; Rakibul & Samia, 2022). Predictive models may also support experimentation operations by forecasting expected outcomes, monitoring risk, and prioritizing test candidates. This convergence reflects a broader conceptual shift in marketing analytics from isolated analytical tasks toward end-to-end decision architectures. In global organizations, integrated systems enable consistent decision logic while accommodating local experimentation and data heterogeneity. The interaction between analytics and experimentation thus shapes how marketing knowledge is generated, refined, and institutionalized across markets (Abdul, 2023; Alojail & Bhatia, 2020; Sohel et al., 2022).

Figure 2: AI Predictive Marketing Decision Framework



The literature on predictive analytics in marketing decision-making spans multiple disciplines, methodological traditions, and application contexts, resulting in a fragmented and heterogeneous body of knowledge (Abdulla & Zaman, 2023; Arfan et al., 2023; Zhang & Lu, 2021). Studies differ widely in how predictive analytics is defined, how segmentation is operationalized, and how experimentation is designed and evaluated. Some research emphasizes algorithmic performance, while other work focuses on managerial applicability, system integration, or operational scalability. This diversity creates challenges for synthesizing evidence about how AI-driven segmentation and A/B testing actually support marketing decisions. A systematic review provides a structured approach for organizing this literature by identifying recurring conceptual frameworks, methodological patterns, and empirical evaluation practices (Amin & Mesbaul, 2023; Foysal & Aditya, 2023; Shah et al., 2020). By focusing specifically on predictive analytics as a decision-making mechanism, rather than as a purely technical exercise, such a review highlights how analytical outputs are translated into marketing actions. Examining segmentation and experimentation together is particularly important because these components jointly determine how consumer heterogeneity is recognized and how marketing interventions are validated. The international scope of marketing analytics further underscores the need for synthesis, as studies conducted in different markets may employ similar techniques under different institutional conditions (Delen & Ram, 2018; Hamidur, 2023; Rashid et al., 2023). A systematic review therefore serves as an analytical lens for clarifying definitions, mapping methodological choices, and understanding how predictive analytics structures marketing decision-making across diverse contexts (Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023).

The present study is guided by a set of interrelated objectives that collectively frame how predictive analytics is examined as a structured mechanism for marketing decision-making, with specific emphasis on AI-driven consumer segmentation and A/B testing strategies. The first objective is to define predictive analytics in marketing decision-making as a coherent analytical domain by clarifying how predictive modeling, algorithmic learning, and decision logic interact within modern marketing systems. This objective focuses on establishing conceptual boundaries that differentiate predictive estimation from descriptive reporting and from purely operational automation, while still recognizing that many marketing platforms integrate these functions into unified workflows. The second objective is to systematically identify and categorize the dominant AI-driven approaches used for consumer segmentation, including how segmentation is operationalized from behavioral, transactional, and digital engagement data, and how segments are represented for use in targeting and personalization decisions. Under this objective, attention is directed toward how segmentation is constructed, whether segment structures are static or continuously updated, and how segmentation outputs are translated into actionable marketing rules and performance indicators. The third objective is to examine A/B testing strategies as empirical validation instruments within predictive marketing systems, focusing on how experimentation designs are structured, which marketing elements are typically tested, and how evaluation metrics are selected to support decision approval, scaling, or discontinuation. This objective includes reviewing how test assignment, measurement practices, and decision thresholds shape the interpretation of marketing effectiveness evidence. The fourth objective is to explore the integrated relationship among predictive analytics, consumer segmentation, and experimentation by assessing how predictive models guide test prioritization, how segments inform experimental stratification or heterogeneity assessment, and how experimental outcomes feed back into model refinement within operational decision cycles. The fifth objective is to synthesize the methodological and contextual variations reported across studies, including differences in data sources, modeling techniques, evaluation criteria, and implementation settings, with an explicit focus on international relevance and cross-market applicability. Together, these objectives provide a structured basis for systematically reviewing how predictive analytics, AI-driven consumer segmentation, and A/B testing strategies function as interconnected components of marketing decision-making rather than isolated analytical tasks.

LITERATURE REVIEW

The literature on predictive analytics in marketing decision-making has expanded into a multi-stream domain where model-driven forecasting, AI-enabled consumer segmentation, and controlled experimentation practices collectively shape how firms select, evaluate, and scale marketing actions. Within this body of work, predictive analytics is not treated only as a technical activity that produces scores or forecasts; it is increasingly framed as a decision infrastructure that connects data collection, feature construction, model training, deployment, and evaluation to operational marketing choices (Sarker, 2021). At the same time, the literature remains fragmented across disciplinary traditions. Marketing science studies often prioritize managerial decision logic, targeting outcomes, and market-response measurement, while information systems and computer science contributions emphasize computational architectures, algorithm performance, and scalable implementation. This fragmentation becomes more pronounced when the review centers on AI-driven segmentation and A/B testing strategies, because segmentation research spans classical segmentation theory, clustering and representation learning, and personalization systems, while experimentation research spans randomized controlled trials, online A/B testing platforms, sequential testing procedures, and measurement governance (Gupta et al., 2021). As a result, the literature review in a systematic review must do more than list studies; it must organize evidence into coherent conceptual categories, clarify how key terms are used, and compare methodological choices that influence the validity and comparability of reported findings. Accordingly, this literature review section synthesizes prior research by mapping how predictive analytics supports marketing decisions, how AI-driven segmentation operationalizes consumer heterogeneity for targeting, and how A/B testing strategies generate causal evidence for selecting among competing marketing alternatives (Shamim et al., 2020). The section also highlights how these streams interact within integrated decision cycles in which models propose actions, segmentation structures define who receives what, and experimentation validates incremental effects under real-world constraints.

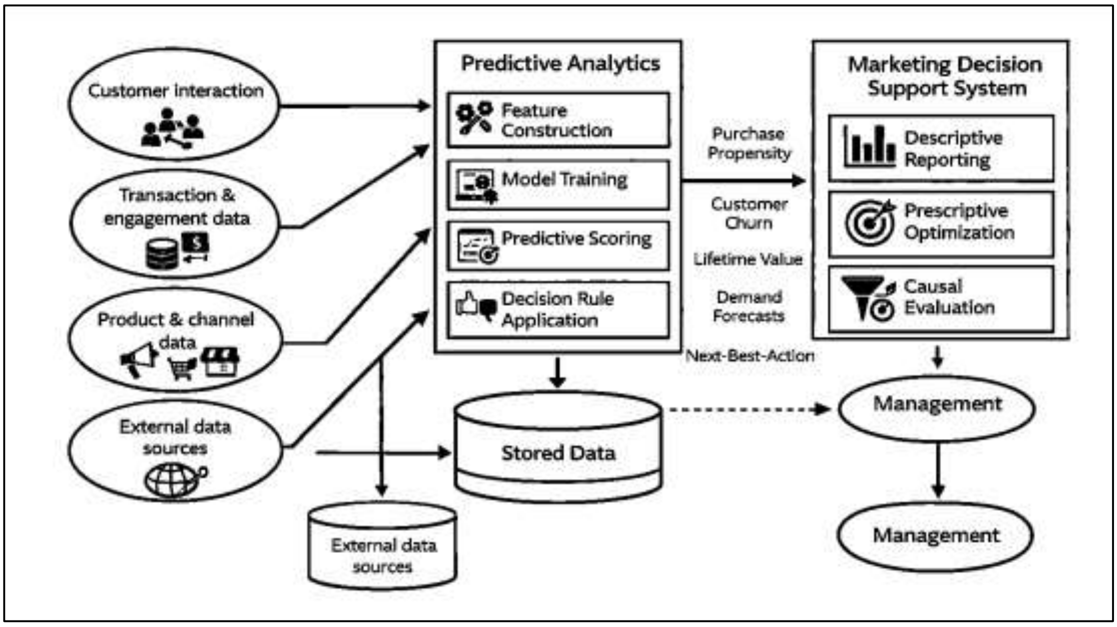
Predictive Analytics in Marketing Decision-Making

Predictive analytics in marketing decision-making can be defined as the structured use of data-driven modeling to produce probability-based estimates that guide managerial actions under uncertainty. In this domain, predictive analytics commonly includes the estimation of purchase propensity, churn likelihood, customer lifetime value, demand levels, and next-best-action recommendations (Niu et al., 2021). These predictive outputs translate consumer signals into quantitative indicators that help marketers decide how to allocate attention and resources across customers, products, and channels. A core conceptual foundation in the literature is the separation of predictive analytics from descriptive analytics. Descriptive analytics focuses on summarizing historical outcomes through reporting, dashboards, and performance indicators, enabling firms to understand what has already happened. Predictive analytics, in contrast, focuses on forecasting or estimating what is likely to happen by identifying patterns in past and current data, thereby enabling proactive decisions. Another key boundary separates predictive analytics from prescriptive analytics. Predictive analytics produces forecasts or likelihood estimates; prescriptive analytics transforms those estimates into action rules or optimization routines that determine what should be done given constraints such as budgets, channel capacity, and strategic priorities (Ghasemaghaei, 2019). This boundary matters because accurate prediction alone does not automatically generate good decisions unless there is a decision rule that connects predictions to costs, benefits, and operational constraints. A third boundary concerns predictive modeling versus causal reasoning. Predictive modeling emphasizes accurate estimation of outcomes and is often evaluated using generalization performance, calibration, and error trade-offs. Causal reasoning emphasizes incremental impact, focusing on how outcomes change when a marketing action is applied. In marketing, this distinction is important because many decisions are interventions that can alter consumer behavior (Ancillai et al., 2019). Therefore, conceptual foundations often treat predictive analytics as a decision-support system that must be clearly positioned in relation to reporting, optimization, and causal evaluation to avoid mismatches between what a model estimates and what a decision requires.

The application literature consistently presents predictive analytics as a central mechanism for supporting marketing decisions across targeting, budget allocation, personalization, customer management, and pricing or promotion design. In targeting decisions, predictive analytics helps marketers determine which customers to contact, when to contact them, and through which communication channel (Amin & Praveen, 2023; Ibne & Kamrul, 2023; Sun et al., 2017). These decisions frequently involve limited resources, contact policies, and heterogeneous consumer responsiveness, making probability-based prioritization valuable. In customer management contexts, predictive analytics supports retention strategies and service interventions by identifying customers who are likely to disengage or churn, then ranking them for outreach based on estimated risk and potential value. Customer lifetime value estimation further links predictive analytics to long-horizon decision-making by prioritizing customers not only by immediate response likelihood, but by expected future contribution over time. Personalization represents another major decision environment, where predictive models and ranking systems select content, product offers, or messaging variants at the level of the individual consumer or the session. This converts marketing from a periodic planning activity into a continuous real-time decision process embedded in digital platforms (Gupta et al., 2019; Haider & Hozyfa, 2023; Zobayer, 2023). Predictive analytics also influences budget allocation and campaign pacing decisions by forecasting performance across audiences, channels, and time windows, enabling more disciplined allocation of spend where returns are expected to be higher. Pricing and promotion decisions use predictive signals to estimate demand sensitivity and likely response patterns, supporting evaluation of alternative price points and promotional mechanics as decision options. Across these contexts, predictive analytics is treated not simply as modeling but as operational decision support: the value of prediction depends on integration into systems that convert scores into actions, track outcomes, and connect performance measurement to marketing execution workflows (Ghasemaghaei et al., 2018).

A widely used conceptual lens in this literature is the decision pipeline, which frames predictive analytics as an end-to-end system that transforms raw data into marketing actions and measurable outcomes. The pipeline is often described as a sequence: data collection → feature construction → model training → scoring or segmentation → decision rule application → outcome realization → evaluation → model refresh (Shabbir & Gardezi, 2020). At the data stage, organizations assemble information from customer records, transactions, engagement logs, and exposure histories. Feature engineering then transforms raw records into predictors, such as behavioral summaries, channel interaction measures, temporal patterns, and context indicators. Modeling produces probability estimates or scores, and these scores become the basis for segmentation, ranking, and prioritization. The decision rule layer converts predictions into operational actions, for example by setting thresholds for contact, selecting offers for personalization, or allocating campaign resources under constraints. The outcome layer captures consumer responses such as conversion, engagement, revenue, retention, or satisfaction. Evaluation then compares expected performance to realized outcomes using business metrics and analytic criteria, and the refresh stage updates features, retrains models, or revises decision rules to maintain performance under changing conditions (Sun et al., 2018). The pipeline perspective is important because it clarifies that predictive analytics is not a single algorithmic output but a system of interconnected steps where performance depends on the coherence among data, modeling, decision rules, and measurement. It also shows how different studies can be compared systematically: one study may focus on improving modeling accuracy, another on improving decision thresholds, another on integrating scoring with experimentation, and another on operational governance. This pipeline framing supports synthesis because it provides a consistent structure for analyzing how predictive analytics is implemented and evaluated as a marketing decision capability (Ducange et al., 2018).

Figure 3: Predictive Marketing Analytics System Framework



The conceptual foundations also emphasize that bias and error can enter predictive marketing systems at multiple points in the pipeline, influencing both predictive performance and the validity of decisions based on model outputs. Data-related problems are a major source of error (Vassakis et al., 2017). Missing values, inconsistent identifiers, measurement lag, and selective observation can distort feature distributions and weaken the link between predictors and outcomes. Measurement lag is particularly relevant in marketing because outcomes such as conversions, repeat purchases, or long-run value may occur after exposure, meaning labels can be incomplete or misaligned with the decision moment. Another critical source of error is leakage, which occurs when a model is trained using information that would not be available at the time of prediction, such as post-outcome variables or downstream signals inadvertently included in the feature set. Leakage leads to overly optimistic accuracy during development and weaker performance in deployment. Drift is another major challenge: consumer preferences, competitive activity, platform algorithms, and macroeconomic changes shift behavioral patterns, meaning relationships learned from historical data degrade when the environment changes (Bumblauskas et al., 2017). Feedback loops are especially important in marketing because model-based decisions alter what data becomes observable. When high-score customers are repeatedly targeted, outcomes reflect both their underlying propensity and the effect of being targeted, which can bias later training data and reinforce the system's existing policy. This issue becomes more severe when prediction is used as an intervention policy without careful alignment to incremental effects. Evaluation practices can also introduce error if metrics are poorly defined, if repeated testing creates inflated false positives, or if instrumentation changes mid-campaign. Collectively, these sources of bias highlight why predictive analytics must be assessed as a system: performance depends on data integrity, temporal validity, model governance, decision rules, and measurement consistency rather than on algorithm choice alone (Bag et al., 2021).

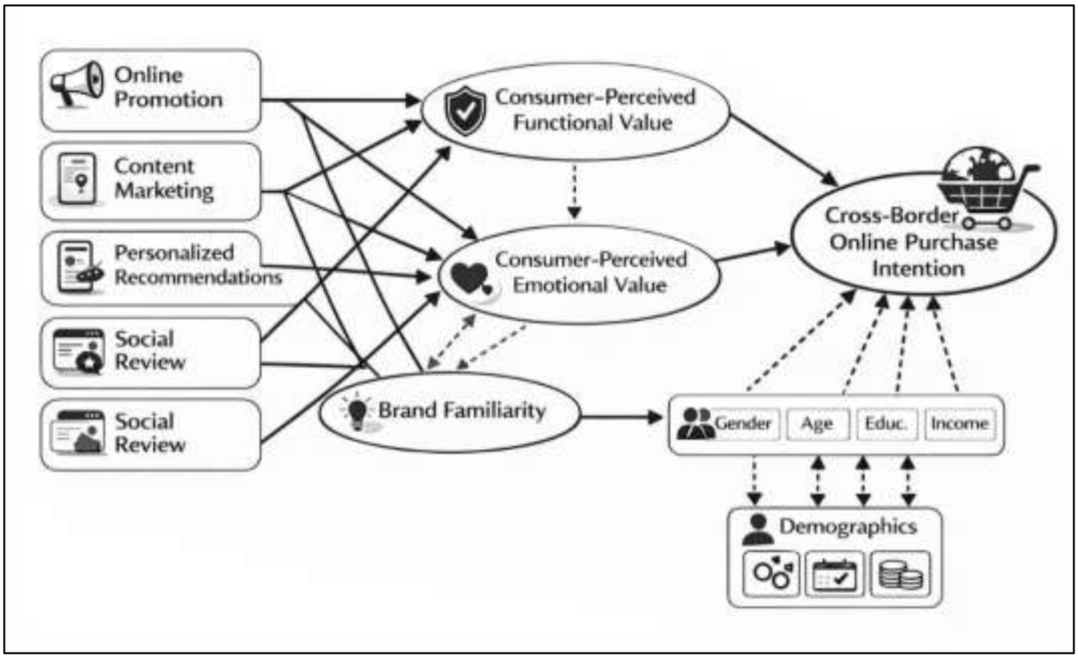
Data Ecosystems and Marketing Analytics Inputs

Marketing predictive analytics operates within a data ecosystem that combines multiple streams of consumer, campaign, and contextual information into a unified decision-support environment (S. Oliveira et al., 2019). Across the literature, first-party data forms the structural backbone of many predictive systems because it captures durable, organization-owned records of customers and transactions. Typical first-party sources include CRM profiles, purchase histories, loyalty program activity, service logs, complaint records, and interaction notes from sales or customer support. These data types provide longitudinal continuity, enabling models to represent the consumer relationship over time through variables such as tenure, repeat purchase cadence, product category breadth, and service experience patterns. Digital behavioral data complements first-party sources by capturing granular traces of what consumers do in digital environments, including clickstream sequences, browsing depth, time-on-page, search queries, app events, cart actions, and navigation pathways. This behavioral layer is highly useful for modeling intent because it reflects immediate interest signals and micro-decisions that precede conversion or disengagement (Pham & Stack, 2018). Campaign exposure data provides another major input stream and includes impressions, opens, clicks, view-through events, frequency, reach, recency, and message delivery characteristics across email, paid media, push notifications, and onsite placements. Exposure data is central for understanding marketing contact intensity and timing, and it enables models to incorporate the fact that consumers do not act in isolation from the messages they receive (L. Sun et al., 2017). Contextual data adds situational meaning to behavior by including device type, operating system, browser, time-of-day, day-of-week, geolocation proxies, store proximity signals, and seasonality markers. These variables account for behavioral variation driven by environment and timing rather than by stable preference alone. Content data extends analytics inputs further by capturing unstructured or semi-structured information such as product reviews, customer messages, chat transcripts, call center summaries, creative text, images, video frames, and creative attributes. Content data is used to model sentiment, topic emphasis, complaint themes, persuasion style, and the match between creative elements and consumer preferences. Taken together, these data types reflect a layered marketing measurement system: first-party records describe who the customer is and what they have done historically, behavioral logs describe what the customer is doing now, exposure records represent what marketing touches occur, contextual variables represent the conditions under which actions occur, and content signals represent what messages and meanings circulate in the interaction (Yu et al., 2019).

Feature engineering represents the bridge between raw marketing data streams and the predictive models that drive decision-making. A recurring pattern in the literature is the construction of summary aggregates, particularly recency-frequency-monetary style features and related behavioral totals. These features convert transactional and engagement histories into interpretable signals such as time since last purchase, number of purchases in a window, total spend, average order value, discount share, and repeat rate (Zhang et al., 2017). Similar aggregates appear for digital engagement, such as sessions per week, product views per session, cart additions, dwell time, and content interactions. Aggregation is valuable because it stabilizes noisy event data and produces consistent signals aligned with managerial thinking about relationship strength, engagement intensity, and responsiveness. A second pattern is sequence feature design, which retains temporal structure rather than collapsing history into totals. Sequence features include session order, transitions between pages or categories, time between events, dwell-time sequences, revisit cycles, and the progression from search to view to cart to purchase. These features better represent consumer journeys and enable models to capture timing effects, momentum, and drop-off points. A third pattern involves interaction features that explicitly combine variables across domains, such as channel-by-segment indicators, offer-by-context markers, device-by-message interactions, and frequency-by-recency combinations. These engineered interactions reflect the idea that consumer response depends on the joint configuration of who the consumer is, what message appears, where it appears, and when it appears (Dai et al., 2019). A fourth pattern is the use of embeddings and latent representations to compress large categorical spaces and unstructured content into dense vectors. In marketing systems, embeddings commonly represent users, products, creatives, and queries in a shared latent space where similarity approximates behavioral or preference closeness. These representations support both prediction and segmentation by providing compact features that capture complex relationships among entities. Another persistent feature-engineering issue is class imbalance, especially in conversion prediction, churn events, fraud-like behaviors, or rare high-value purchases. Many marketing outcomes are sparse, and feature engineering practices often include careful label definition, sampling strategies, threshold-aware features, and cost-sensitive weighting to reduce the dominance of non-events in training. Feature creation also includes leakage controls, since some engineered variables can accidentally encode post-outcome information through timing misalignment or improper windowing (Abella et al., 2017). Across these patterns, the literature treats feature engineering as a primary determinant of predictive usefulness: engineered features define what the model can "see," shape interpretability, and influence whether predictions translate into stable and actionable decision rules.

Data governance is repeatedly highlighted as a decisive layer that shapes the feasibility, credibility, and comparability of predictive analytics in marketing. Privacy constraints and consent boundaries determine what data is collected, how it is retained, and which linkages are permitted across systems (White et al., 2018). Marketing datasets frequently involve personal and behavioral information, and governance constraints influence whether models rely on first-party identifiers, whether data is aggregated or anonymized, and whether sensitive categories are excluded. Consent design influences representativeness because opt-in and opt-out patterns can systematically alter the observed population, which affects both training distributions and the meaning of predictive outputs. Identity resolution is another major governance variable because consumers engage across devices, browsers, and channels, and linking these interactions into a single customer view requires matching systems and rules. When identity resolution is incomplete, behavioral and exposure histories fragment across identities, producing underestimation of frequency, distorted journeys, and inconsistent personalization. Governance rules also shape how deterministic and probabilistic matching is handled, which affects the reliability of customer-level features and the interpretability of segments. Data granularity decisions further influence modeling because marketing outcomes can be defined and predicted at different levels: user-level, household-level, session-level, impression-level, store-level, or campaign-level. Each level changes what counts as an observation, what features are meaningful, and how evaluation metrics are interpreted (Kitsios et al., 2017). For example, user-level modeling captures relationship history, while session-level modeling captures immediate intent; campaign-level modeling captures aggregate lift and pacing dynamics. Label definition consistency is another central governance issue, particularly for conversion windows, attribution choices, and outcome timing. A conversion defined as a purchase within 24 hours after an exposure represents a different behavioral phenomenon than a purchase within 30 days, and attribution rules determine whether outcomes are linked to the last touch, multiple touches, or an incrementality framework. Inconsistent labels reduce comparability across studies and can produce models that optimize for different behaviors under the same name. Governance also extends to measurement instrumentation, where event definitions and tracking mechanisms must remain consistent to ensure that shifts in metrics reflect real changes rather than logging changes (Kitchens et al., 2018). Together, privacy rules, identity resolution policies, granularity decisions, and label definitions constitute the governance framework that determines not only what data enters predictive systems but also how meaning is assigned to features, outcomes, and performance claims within marketing analytics.

Figure 4: Marketing Predictive Analytics Input Framework



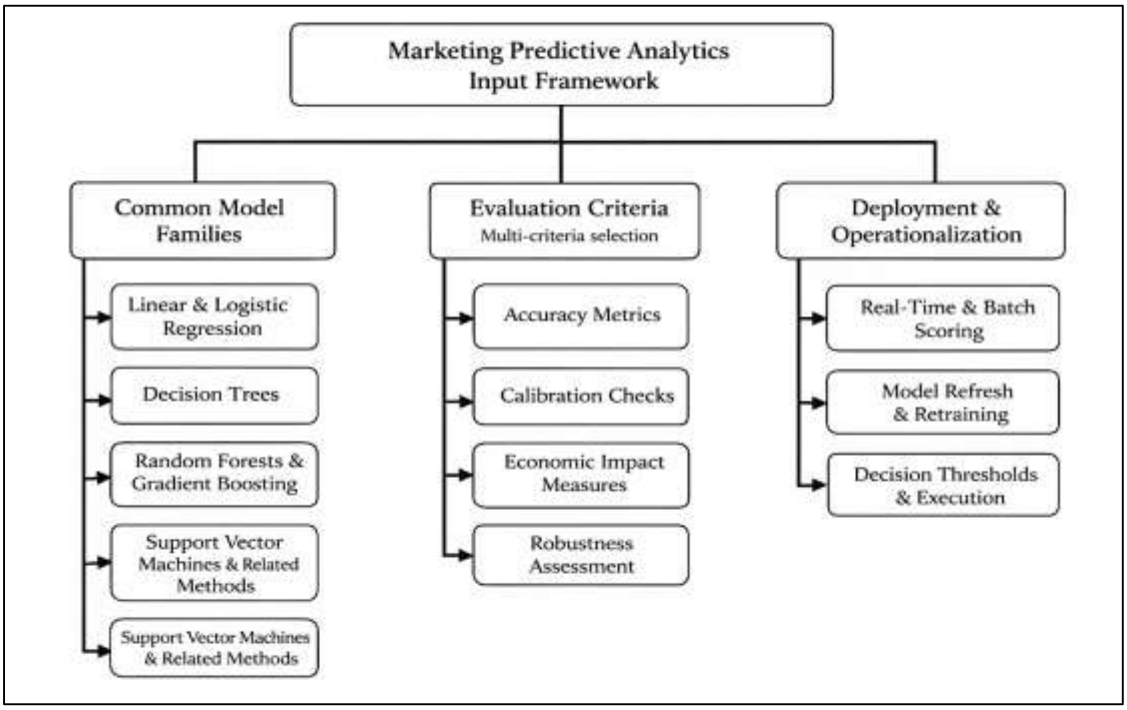
When synthesized, the literature portrays marketing predictive analytics inputs as an integrated system in which data types, feature engineering, and governance rules co-produce what predictions mean and how decisions are supported (Song et al., 2021). Data types provide coverage across relationship history, real-time intent, marketing exposure, situational context, and message content, yet each data type carries different strengths and risks. First-party records offer stability and longitudinal depth, digital behavioral logs provide immediacy and granularity, exposure data captures contact intensity and timing, contextual variables encode situational constraints, and content data captures meaning, sentiment, and creative characteristics. Feature engineering converts these heterogeneous sources into a coherent representation space by building aggregates that stabilize noise, sequences that retain temporal structure, interactions that encode conditional response patterns, and embeddings that compress complex entities and unstructured content. At the same time, feature engineering practices interact directly with governance constraints. Privacy boundaries limit the detail of available signals, identity resolution rules determine whether features represent complete journeys or fragmented fragments, granularity choices determine the unit of prediction and the interpretability of outputs, and label definition choices determine what the model is actually learning to predict (Kassem & Succar, 2017). This synthesis implies that "model performance" cannot be interpreted as a purely algorithmic achievement because it is inseparable from input design: a highly accurate model may reflect strong data coverage and clean labels, while weaker performance may reflect fragmented identity, restrictive consent, or noisy instrumentation. The integrated view also clarifies why comparability across studies varies (Brandt et al., 2017). Two studies that both claim to predict conversion can differ substantially if one uses impression-level exposure histories with strict attribution windows and another uses user-level histories with broader conversion windows and different identity matching rules. Similarly, segmentation inputs vary based on whether features rely on stable first-party relationship variables or on volatile behavioral logs and content embeddings. The literature therefore treats marketing analytics inputs as a socio-technical architecture: data sources provide signals, feature engineering defines representation, and governance defines boundaries and meanings (Bradlow et al., 2017). Under this architecture, methodological rigor depends on clear temporal alignment, leakage control, consistent outcome definitions, and transparent description of identity resolution and granularity. This systems perspective organizes how marketing predictive analytics is reviewed, because it places the focus on how evidence is generated from inputs rather than on algorithms alone, and it explains why results depend on the quality, structure, and governance of the underlying data ecosystem.

Predictive Modeling Approaches Used for Marketing Decisions

The literature on predictive modeling for marketing decisions commonly organizes supervised learning approaches into a set of recurring model families that balance interpretability, predictive power, and operational feasibility (Bradlow et al., 2017). Linear and logistic regression approaches are frequently treated as foundational baselines because they provide transparent coefficient-based explanations and stable performance when relationships between predictors and outcomes are approximately additive. In marketing decision contexts such as response prediction, churn risk estimation, and propensity scoring, these models are valued for their clarity in communicating which variables contribute to conversion likelihood or defection risk, and for their suitability in regulated or governance-sensitive environments where explanation and auditability matter. Decision trees extend this interpretability logic by producing rule-like structures that mirror managerial heuristics, translating patterns into explicit decision paths that are easy to explain to marketing stakeholders. However, single-tree models often show instability and limited accuracy when data is noisy or nonlinear, which contributes to the prominence of ensemble methods. Random forests and gradient boosting models appear widely because they improve generalization by aggregating many trees, capturing nonlinearities and interactions among consumer behavior, exposure intensity, and contextual factors (Gandhmal & Kumar, 2019). In digital marketing environments where response behavior depends on complex joint conditions such as timing, channel, and creative attributes, boosted ensembles are frequently used to capture such conditional patterns without requiring manual interaction engineering. Support vector machines and related margin-based methods appear in studies emphasizing high-dimensional classification, especially when the feature space includes many sparse indicators or engineered representations. These methods often appeal in tasks where separation boundaries are complex and where regularization strength must be controlled to reduce overfitting. Neural network approaches appear most prominently in contexts involving high-dimensional signals and sequential consumer behavior, where the modeling objective includes learning representations from clickstreams, session sequences, textual content, or multimodal features. In these studies, neural architectures function less as direct analogs to classical marketing models and more as pattern-learning systems that can compress complex input structures into latent representations usable for prediction and personalization (Ullah et al., 2019). Across these supervised learning families, a recurring theme is that model choice is shaped by the decision environment: interpretability and governance favor simpler baselines, while performance and scale favor ensembles and neural approaches, especially when marketing decisions depend on heterogeneous behavior patterns that are not well captured by linear assumptions.

Studies evaluating predictive models for marketing decisions typically adopt multi-criteria selection logics that extend beyond a single measure of accuracy. Accuracy metrics remain central because they provide standardized ways to compare models' ability to discriminate between responders and non-responders, churners and retainers, or high-value and low-value outcomes (Fitriyani et al., 2020). Common evaluation practices include discrimination-focused measures such as ROC-style comparisons, probabilistic scoring measures such as loss-based evaluations, classification measures based on precision and recall trade-offs, and calibration-oriented checks that assess whether predicted probabilities match observed event rates. The literature treats calibration as particularly important in marketing because predicted probabilities often feed decision thresholds, budget pacing rules, and risk-sensitive targeting policies; poorly calibrated probabilities can lead to over-contacting low-likelihood customers or under-investing in valuable segments. At the same time, marketing-focused studies regularly emphasize that technical accuracy alone does not guarantee decision usefulness. As a result, business-oriented evaluation metrics are frequently integrated into model selection, including lift-style comparisons that show how targeting the top-ranked portion of a population improves response relative to random selection (Sun et al., 2020). Studies also evaluate models through incremental revenue proxies, expected margin contributions, and profit curves that incorporate the costs of contact, incentives, media spend, and operational capacity. These measures link model performance to decision payoffs by converting ranking quality into estimated business value under realistic constraints. Another recurring evaluation theme concerns robustness. Marketing environments are dynamic, and models can degrade when consumer preferences shift, channels evolve, competitors change tactics, or measurement systems change. Robustness evaluation therefore includes assessing stability under drift conditions, monitoring performance across time slices, and comparing error variation across consumer segments, channels, and regions. Segment-level error variation matters because a model that performs well on average can perform poorly for strategically important groups, producing inconsistent experiences and biased resource allocation. Many studies therefore treat model selection as a trade-off between global accuracy, local stability, business impact, and reliability under changing conditions (Speiser et al., 2019). This multi-criteria approach frames model evaluation as a decision-aligned process rather than a purely statistical competition, and it reinforces the idea that marketing predictive analytics is assessed through the combined lens of discrimination, probability quality, economic value, and operational reliability.

Figure 5: Marketing Predictive Modeling Framework Overview



The literature on marketing predictive modeling consistently positions deployment and operationalization as essential components of model effectiveness, because the value of prediction depends on how predictions are delivered, timed, and translated into actions. Real-time scoring appears prominently in digital environments where decisions occur at the moment of interaction, such as choosing a recommendation, selecting an offer, deciding which creative to display, or prioritizing a service intervention during a session (Mosavi et al., 2020). In these settings, models must score quickly using low-latency features that are available at decision time, and they must integrate with delivery systems that execute actions immediately. Batch scoring appears widely in CRM and campaign planning contexts where decisions are made on daily, weekly, or monthly cycles, such as creating outreach lists, prioritizing retention calls, or allocating email campaigns. Batch scoring supports richer feature sets that can include longer histories and more complex aggregates, and it is often paired with operational processes that schedule contact policies and capacity limits. Model refresh frequency and retraining triggers represent another operationalization dimension. Marketing behavior changes over time, so studies often emphasize monitoring performance decay and updating models using time-based retraining schedules or performance-driven triggers. Refresh frequency is connected to data availability, drift speed, and business risk tolerance: frequent updates may improve relevance but increase operational complexity, while infrequent updates may simplify governance but risk outdated scoring. Decision thresholds are also treated as operational mechanisms rather than purely statistical settings (Sarker, 2021). Thresholds convert predicted probabilities into actions and determine how many customers are contacted, how budgets are allocated, and how incentives are distributed. Threshold selection is therefore tied to budget constraints, channel capacity, customer experience policies, and marginal return considerations, with many studies emphasizing that optimal thresholds vary by campaign objective and cost structure. Finally, human-in-the-loop versus automated execution appears as a key operational trade-off. Human-in-the-loop processes are used when decisions require oversight, explanation, or brand judgment, such as high-stakes customer interventions or sensitive segmentation policies. Automated execution is more common when decisions are frequent, standardized, and tightly integrated with digital delivery systems (Nabipour, Nayyeri, Jabani, & Mosavi, 2020). Across deployment patterns, studies treat predictive modeling as embedded within a decision system that includes data pipelines, scoring frequency, action rules, monitoring processes, and governance checkpoints, emphasizing that predictive performance is inseparable from operational design.

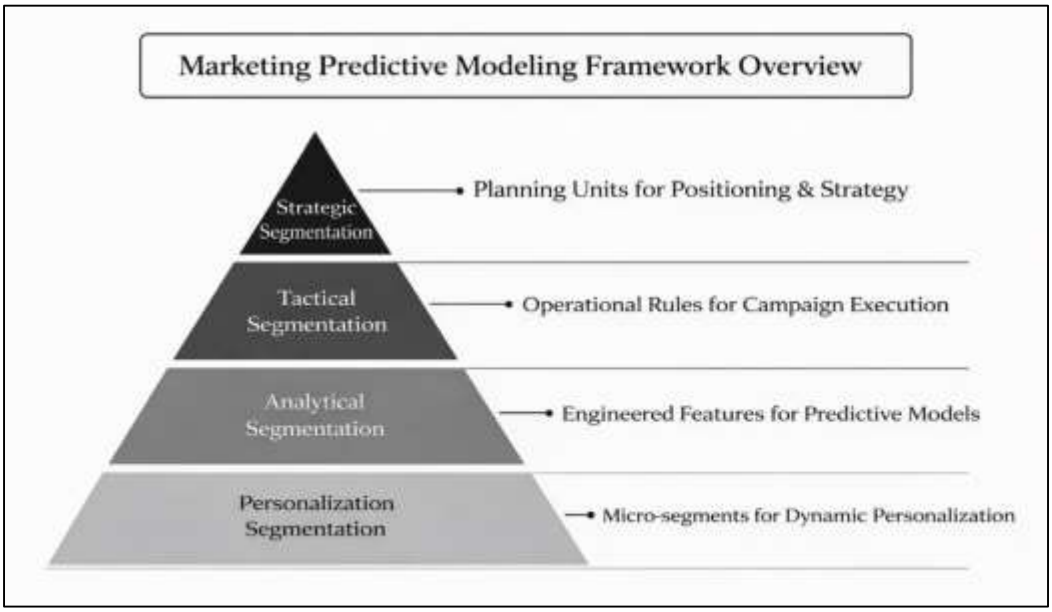
AI-Driven Consumer Segmentation Literature

The consumer segmentation literature consistently frames segmentation as a core mechanism for reducing market heterogeneity into actionable structures that support decision-making across strategic, tactical, analytical, and personalization contexts (Gkikas & Theodoridis, 2021). In strategic segmentation, segments operate as planning units that guide positioning, value proposition design, and market entry logic by identifying groups that differ in needs, preferences, and willingness to pay. Strategic segmentation is closely tied to managerial sensemaking because it creates a shared language for describing the market and aligning product, brand, and channel strategies around distinct consumer profiles. In tactical segmentation, segments function as operational rules for campaign execution, including who is eligible for specific offers, what contact frequency is permitted, which channels should be prioritized, and how budgets are distributed across audience groups. Tactical segmentation is often more dynamic than strategic segmentation because it is shaped by response patterns, campaign fatigue, contact policies, and performance targets. Analytical segmentation plays a distinct role by serving as an input structure for predictive systems: segments become engineered features, strata for model training, or units for performance monitoring (Huang & Rust, 2021). In this role, segmentation supports predictive analytics by summarizing complex consumer histories into compact descriptors that models can use to estimate response, churn risk, or value. Personalization segmentation extends segmentation into high-granularity forms such as micro-segments and latent clusters that are generated and updated continuously based on behavioral signals. Here, segmentation is embedded in digital decision systems where the boundary between "segment" and "individual-level personalization" becomes blurred, as clusters are constructed to support real-time content ranking, offer selection, and recommendation. Across these roles, the literature emphasizes that segmentation is not a single method but a family of practices that connects market understanding to execution (Verma et al., 2021). The same organization may maintain a stable strategic segmentation for long-term planning, a tactical segmentation for current campaign governance, an analytical segmentation for modeling and monitoring, and a personalization segmentation that changes rapidly based on fresh interaction data. This multi-role view clarifies why segmentation is repeatedly treated as a decision infrastructure rather than only a descriptive taxonomy: segments structure how resources are allocated, how performance is evaluated, and how heterogeneous consumer responses are translated into repeatable marketing actions (Khan & Iqbal, 2020).

Classical segmentation research establishes the foundational logic that markets contain meaningful subgroups and that marketing effectiveness improves when offerings and communications are aligned with subgroup differences (De Caigny et al., 2021). Demographic and geographic segmentation approaches organize consumers using observable characteristics such as age, income proxies, region, and household structure, providing simple and operationally convenient groupings that can be activated through media buying and list management. Psychographic segmentation extends this by incorporating values, lifestyles, motivations, and attitudes, typically captured through surveys or inferred through behavior, with the intent of describing deeper drivers of preference beyond demographic descriptors. Behavioral segmentation shifts the organizing principle toward what consumers do rather than who they are, using purchase histories, engagement patterns, channel usage, and recency-frequency-style behaviors to identify groups that differ in relationship strength, product interests, and responsiveness (Debnath et al., 2021). Behavioral approaches often show strong managerial usefulness because they connect directly to observable actions that marketing interventions can influence. Model-based segmentation emerged as a methodological advance by treating segmentation as an estimation problem rather than a manual categorization task. Latent class and mixture-model approaches infer segment membership probabilistically based on observed responses or choice patterns, enabling "soft assignment" where consumers have membership probabilities across segments rather than being forced into a single category. This probabilistic structure supports more nuanced decision rules, such as targeting consumers with high probability of belonging to a high-response segment or designing campaigns that account for membership uncertainty. Classical segmentation traditions also emphasize that segments must be measurable, substantial, accessible, differentiable, and actionable, which keeps segmentation anchored to marketing execution rather than purely statistical group discovery. Even in traditional frameworks, the literature highlights practical tensions: demographic segments can be easy to activate yet weakly predictive of behavior, psychographic segments can be rich yet expensive to measure and maintain, and behavioral segments can be highly predictive yet sensitive to short-term fluctuations and data availability (Grewal et al., 2021). Model-based approaches address some limitations by providing statistical discipline and uncertainty estimates, yet they can introduce interpretability challenges because probabilistic membership and latent structures require translation into manager-friendly profiles. Overall, classical segmentation literature provides the conceptual base that AI-driven segmentation builds upon: it defines what a segment is for, how segments support decisions, and why methodological rigor and managerial interpretability must be balanced when segmentation is used as a foundation for targeting and positioning.

AI-driven segmentation literature expands segmentation practice by applying modern unsupervised learning, representation learning, deep clustering architectures, and hybrid approaches that integrate prediction with discovery (Sheikh et al., 2019). Unsupervised learning methods remain central because segmentation often begins without labeled "true" segment outcomes. Widely used approaches include partitioning methods that group consumers by minimizing within-cluster differences, hierarchical methods that build nested group structures, density-based methods that identify clusters with irregular shapes and isolate noise, and probabilistic mixture models that support soft membership and overlapping segments. AI-driven segmentation extends these foundations by incorporating representation learning pipelines in which high-dimensional behaviors, products, and content interactions are transformed into latent embeddings before clustering is performed. In this pipeline, embeddings act as compact features that capture similarity patterns across consumers based on co-interaction structure, browsing pathways, purchase sequences, or content preferences. Dimensionality reduction often appears as a bridging step to stabilize clustering, improve separation, and reduce noise, with methods that compress features into lower-dimensional spaces where segments can emerge more cleanly (Dutta & Mitra, 2017). Deep clustering architectures push this further by learning representations and clusters jointly, often using autoencoder-like structures that reconstruct input signals while shaping latent spaces to encourage separable segment structure. This approach is particularly common when consumer data is sparse, sequential, or multimodal because deep encoders can learn nonlinear transformations that surface meaningful segmentation structure not visible in raw aggregates. Sequential embeddings are used to represent consumer journeys, enabling segmentation based on temporal patterns such as exploration-to-purchase pathways, churn precursors, and engagement cycles. Hybrid segmentation approaches integrate supervised response modeling with unsupervised discovery by either using predicted outcomes as features for clustering or using segment membership as a constraint or regularizer in predictive models. In these hybrids, segmentation does not merely describe consumers; it shapes decision logic by determining which consumers are treated similarly, how decision thresholds vary by group, and how personalization policies are constrained to maintain consistency and governance (Sjödin et al., 2021). AI-driven segmentation therefore shifts segmentation from a periodic market-research activity toward a continuously computed component of operational decision systems, with segments that can be refreshed frequently, activated in real time, and linked directly to campaign and platform execution.

Figure 6: Consumer Segmentation Framework for Marketing



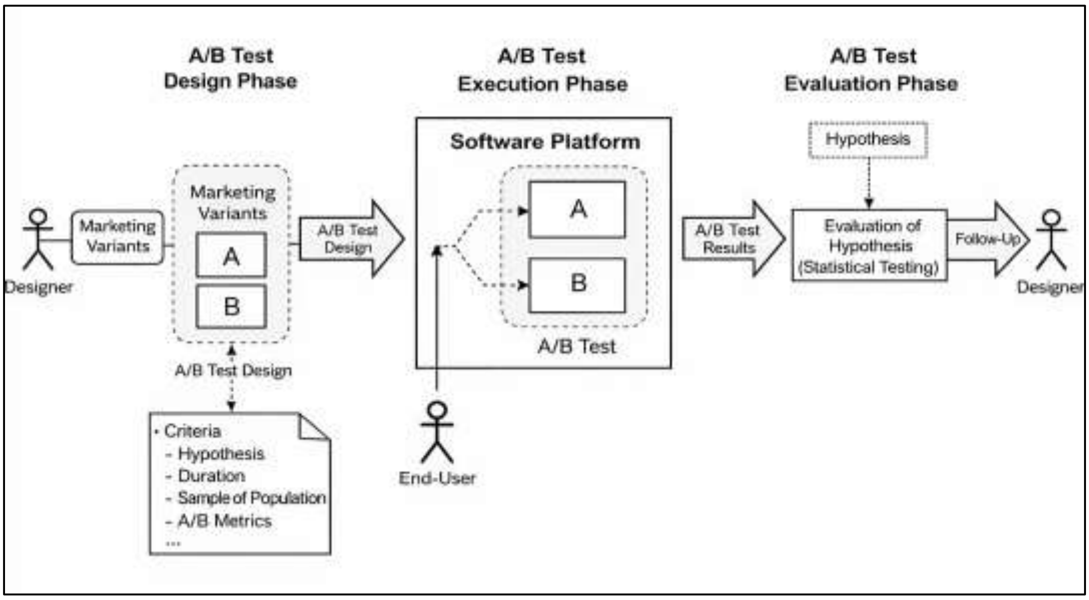
The literature on segmentation evaluation emphasizes that segmentation quality must be judged using both internal statistical criteria and external decision-oriented validation, especially when AI techniques generate complex or rapidly changing segment structures. Internal evaluation commonly focuses on cohesion and separation logic: good segments display high similarity within clusters and clear differences between clusters, with indices that quantify compactness and distance among clusters (Campbell et al., 2020). These internal measures help compare alternative clustering configurations and detect degenerate solutions, yet they do not guarantee marketing usefulness because segments can be statistically clean while offering little actionable differentiation. External validation addresses this by testing whether segments differ meaningfully in outcomes that matter for marketing decisions, such as response rates, conversion likelihood, retention patterns, average spend, product affinity, channel preferences, and campaign fatigue sensitivity. Segment-level response differences support the claim that segments represent behavioral heterogeneity relevant to targeting and offer design. Stability over time is another major criterion because marketing systems require consistent segment definitions for planning, performance tracking, and governance. AI-driven segmentation can change as new data arrives, so the literature evaluates stability through measures of membership persistence, segment drift, and the reproducibility of segment profiles across time windows (Talati et al., 2021). Actionable interpretability is repeatedly highlighted as a practical necessity: segments must be named, described, and communicated so that marketing teams can design creatives, set policies, and explain why different groups receive different actions. Interpretability mechanisms often begin with segment profiling, which ranks the features that most differentiate each segment and summarizes typical behaviors, product preferences, and engagement patterns. Model explanation approaches are used to justify boundaries and membership assignment, particularly when representation learning produces latent features that are not directly human-readable (Brotspies & Weinstein, 2019). Business translation then maps algorithmic clusters to marketing personas by converting statistical patterns into narratives that align with campaign planning language, such as "deal-driven repeat buyers," "research-heavy browsers," or "high-service-risk customers." This translation step is essential because segmentation becomes operational only when it can be embedded in targeting rules, contact strategies, and measurement dashboards. The literature also emphasizes that interpretability is inseparable from governance: when segmentation affects access to offers, service levels, or pricing exposure, organizations require auditable reasoning and consistent profiling to maintain accountability (Hassani et al., 2020). Taken together, evaluation and interpretability research treats AI-driven segmentation as a decision artifact that must satisfy statistical rigor, business relevance, temporal stability, and communicability, reinforcing the view that segmentation is valuable when it performs well as part of a broader marketing decision system rather than as an isolated clustering exercise.

A/B Testing and Experimentation Strategies in Marketing

A/B testing in marketing is commonly defined as a controlled experiment in which units such as users, sessions, households, or regions are randomly assigned to different conditions in order to estimate the causal effect of a marketing action on a measurable outcome (Olsson et al., 2017). The literature treats random assignment as the defining property because it creates comparable groups, enabling observed differences in conversion, revenue, or engagement to be interpreted as effects of the intervention rather than artifacts of selection bias or confounding. This causal interpretation is central to marketing decision-making because many marketing choices are interventions that actively change consumer experiences, and correlation-based prediction alone cannot reliably establish whether a specific action caused an improvement (Fabijan et al., 2018). Experimentation is therefore positioned as a validation mechanism that supports decision approval, rollout, and scaling by providing an empirical basis for choosing between alternatives. Marketing studies describe A/B testing as particularly important in digital environments where interactions are measurable and changes can be deployed rapidly across user interfaces, messaging systems, and recommendation engines. Typical marketing targets include creative variants such as image and copy combinations, email subject lines and send-time policies, landing page layout variations, and differences in call-to-action placement or content density. Experiments also test pricing displays, discount framing, and promotion thresholds, as well as changes in recommendation layouts and ranking logic that influence consumer discovery and basket composition. In addition, A/B testing is increasingly used to evaluate targeting rules and personalization strategies, where the "treatment" may be a policy that selects offers or content based on predicted propensities or segment membership (Viglia et al., 2021). Within this literature, experimentation is often portrayed as a complement to predictive analytics: predictive models propose which action may work best, while experiments provide the causal evidence needed to verify whether that proposal produces incremental value under real operational conditions. This emphasis on causal validation explains why experimentation is described as a core capability in marketing systems rather than merely a research technique, because it serves as an institutional mechanism for learning what works, codifying evidence, and reducing decision uncertainty in settings where consumer behavior is heterogeneous and marketing outcomes are influenced by many simultaneous factors (Orazi & Johnston, 2020).

The experimentation literature documents a range of design variants that extend beyond the classic two-arm A/B test, reflecting the complexity of marketing actions and the need to evaluate multiple factors under realistic constraints. Classic A versus B tests remain common because they are simple to implement, easy to interpret, and well-suited to evaluating a single change such as a new subject line or a modified landing page (Schermann et al., 2018). However, marketing systems often involve multiple interacting design elements, which motivates multivariate and factorial experiments that test combinations of factors simultaneously. These designs support more efficient learning by estimating main effects and interactions, allowing marketers to understand whether an improvement depends on a specific pairing of creative and layout or whether factors act independently. Multi-armed testing extends experimentation to settings with many competing variants, such as multiple creatives or pricing frames, where the aim is to compare several options in parallel rather than sequentially. Some studies describe multi-armed approaches as useful when creative production generates many alternatives, though they introduce additional complexity in controlling error rates and ensuring adequate sample sizes for each arm (Mariani & Nambisan, 2021). Cluster randomization designs appear when individual-level randomization is impractical or when contamination is likely. In marketing, clusters can be stores, regions, time blocks, or sales teams, enabling experiments that evaluate store-level promotions, regional media strategies, or operational policy changes. Geo experiments represent another design class used to evaluate media mix and regional marketing impact, where treatments are assigned to geographic units to estimate lift in sales or brand outcomes while accounting for regional heterogeneity and macro-level fluctuations (Ren et al., 2017). The literature emphasizes that design choice depends on the unit of intervention, the risk of spillover effects, operational feasibility, and measurement infrastructure. When interventions are exposed at the interface level, user-level randomization is feasible; when interventions are broadcast at a regional level or applied through operational procedures, cluster or geo designs are more appropriate. The methodological diversity across designs reflects the broader point that marketing experimentation is not a single standardized practice but a portfolio of experimental strategies selected to match the structure of marketing actions, the risk of interference, and the organizational need for interpretable evidence (Van Kerrebroeck et al., 2017).

Figure 7: Marketing A/B Testing Process Framework



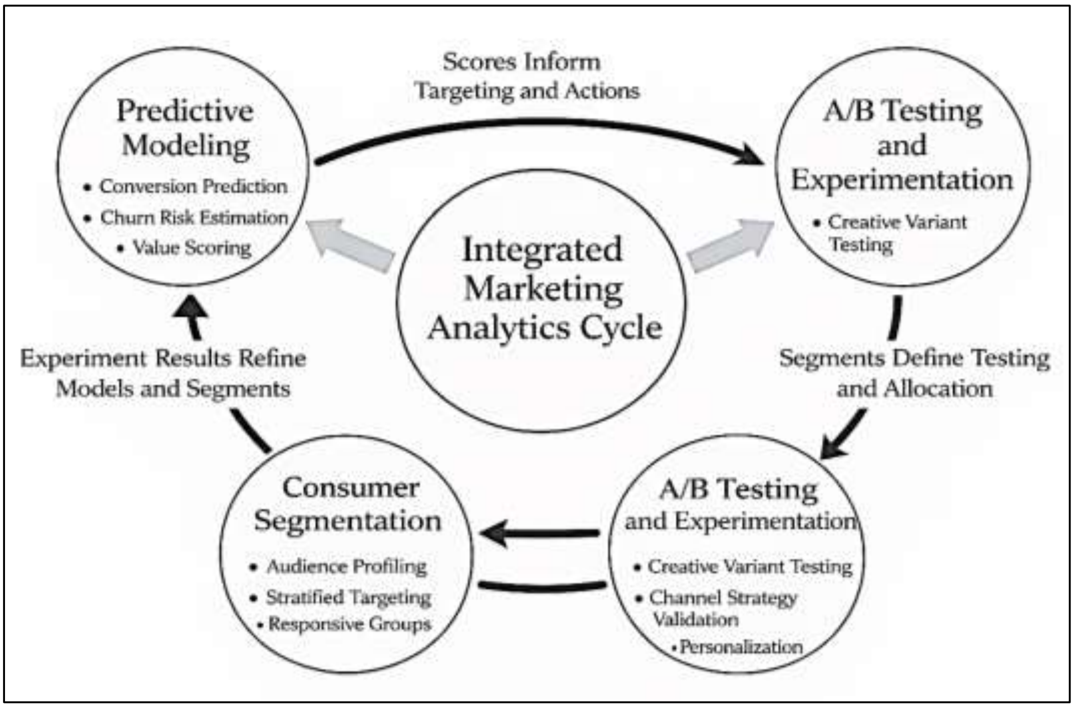
Segmentation and A/B Testing in Decision Cycles

The literature increasingly portrays marketing analytics as an integrated decision cycle in which predictive models, consumer segmentation, and A/B testing operate as interdependent components rather than isolated techniques (Zimmermann et al., 2017). A common integration pattern begins with a predictive model that estimates an outcome such as conversion likelihood, churn risk, or expected value, then uses these scores to select high-priority users for marketing contact under budget and capacity limits. Within this pattern, prediction functions as a filtering and ranking mechanism that determines who enters the action space, while experimentation functions as a validation mechanism that determines which action performs best once the audience is selected. Many studies describe workflows where high-propensity users are exposed to competing offer variants, creatives, or channel treatments through controlled tests, enabling the organization to optimize both "who to target" and "what to show" within a single operational cycle. Another integration pattern uses segmentation to define strata before experimentation begins (Li et al., 2020). Here, segments represent groups expected to differ in baseline behavior or responsiveness, and A/B tests are executed within each stratum to estimate segment-specific effects and reduce variance through structured comparison. This stratified logic supports more granular decisions because it enables marketers to compare which offers work best for which segments rather than relying on a single average effect. A third integration pattern emphasizes feedback from experimentation into predictive systems. In this pattern, experiment results are used to update targeting thresholds, revise eligibility rules, and refine segment definitions, especially when experimental evidence shows that certain segments respond differently or that predicted propensities do not align with incremental impact. Across these integration patterns, the literature treats decision cycles as iterative loops connecting modeling, action, measurement, and refinement. Prediction provides operational scale and prioritization, segmentation provides structure and heterogeneity control, and experimentation provides causal evidence for selecting among alternatives (Panicucci et al., 2020). The studies collectively show that the strongest decision-cycle designs are those that define explicit handoffs between these components—how scores become targeting policies, how segments become test strata, and how experimental evidence becomes updated rules—thereby converting analytic outputs into repeatable decision routines grounded in measurable outcomes.

A major theme in studies linking predictive analytics and experimentation is the distinction between predicting outcomes and predicting incremental impact. In many marketing contexts, a high likelihood of purchase does not necessarily indicate that marketing caused the purchase; some consumers would buy regardless of exposure, while others require persuasion (Bauters et al., 2018). This distinction motivates incremental response frameworks that separate "likely buyers" from "persuadable buyers" by focusing on how outcomes change under treatment compared to control. Uplift modeling and related incrementality approaches provide a formal bridge between predictive analytics and experimental design by modeling treatment effect differences at the individual or segment level. Instead of predicting conversion probability alone, uplift modeling estimates the difference between conversion probability when exposed to a marketing action and conversion probability without exposure. This difference-oriented objective aligns directly with targeting decisions because it identifies the consumers for whom the intervention produces the greatest incremental benefit rather than simply identifying consumers who are most likely to convert. Many studies describe using experimental labels from randomized tests to train and evaluate uplift models, allowing the targeting policy to be optimized for incremental gain (Letourneau-Guillon et al., 2020). This approach changes model evaluation and decision logic: the relevant success criterion becomes incremental lift or profit rather than pure predictive accuracy. Studies also compare targeting policies by simulating or measuring how different selection rules perform relative to a baseline, treating the policy itself as the object of evaluation rather than the model as an abstract predictor. Incrementality frameworks further influence segmentation because segments can be constructed around responsiveness types—such as persuadable, sure-thing, lost-cause, or negatively affected groups—supporting differentiated treatment rules that avoid unnecessary spending on consumers who would purchase anyway or who react adversely. Overall, the incremental impact literature reframes the link between predictive analytics and experimentation by emphasizing that marketing decision-making requires causal quantities when interventions are involved. This reframing clarifies why A/B testing is not merely a post-hoc evaluation step but a data-generating mechanism that enables models to learn intervention responsiveness and supports targeting strategies that prioritize persuasion effects over correlation-based likelihood (Frangopol et al., 2019).

Personalization is frequently presented in the literature as a combined mechanism that unifies predictive analytics, segmentation, and experimentation into a single operational logic. In personalization systems, an algorithm selects a content variant, product recommendation, creative layout, or offer for each user or session, effectively acting as a decision policy that maps user and context features to an action (Hennig et al., 2017). This policy perspective changes the analytic task from predicting a static outcome to choosing an action that maximizes an objective under uncertainty. Many studies describe personalization pipelines in which predictive models generate scores for multiple candidate actions, rank alternatives, and choose the highest-scoring option subject to constraints such as inventory, budget, contact frequency, or fairness rules. Segmentation then plays a complementary role by introducing structure and governance into personalization. Segment membership can constrain what options are eligible, enforce consistency in messaging, or provide guardrails that prevent overly volatile individual-level decisions. Segments also support heterogeneity analysis by allowing marketers to monitor performance by group, ensuring that personalization benefits do not concentrate in only certain consumer types while harming others. A/B testing appears as the main method for evaluating personalization policies against baselines, such as a default ranking system, a rules-based offer policy, or a simpler segmentation-driven strategy (Saha et al., 2021). Rather than testing a single creative variant, experiments evaluate the effect of adopting a personalization policy, comparing outcomes when users receive algorithm-selected actions versus when they receive standard actions. Studies emphasize that this evaluation is essential because personalization systems can create complex feedback loops: the algorithm's choices shape user behavior, which then becomes the data used for future learning. Controlled tests help isolate whether the policy produces incremental value relative to alternative policies. The literature also shows that personalization decisions depend on strong measurement governance because outcomes may be delayed and because multiple exposures can interact over time. Within this integrated framing, predictive analytics provides the scoring and ranking engine, segmentation provides manageable structure and interpretability, and experimentation provides the causal evidence needed to justify the policy as a superior decision mechanism (Cai et al., 2019). This explains why personalization is often described as the operational arena where prediction, segmentation, and experimentation converge into a unified marketing decision cycle.

Figure 8: Integrated Marketing Analytics Decision Cycle



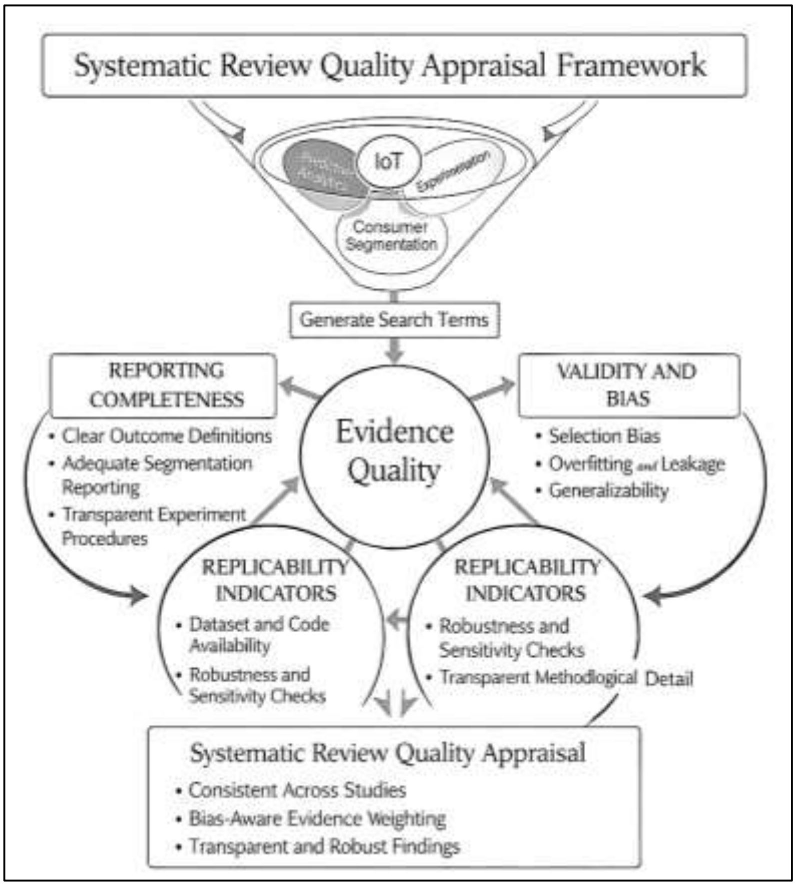
A recurring focus in studies examining the analytics–segmentation–experimentation link is how empirical evidence is translated into concrete marketing actions. One widely documented translation process involves converting statistical evidence from A/B tests into rollout decisions. Here, experimental outcomes determine whether a creative variant, offer, or policy is deployed more broadly, retained as a default, or discontinued (Caicedo et al., 2017). The translation from test results to action often requires decision thresholds that combine statistical criteria and business criteria, because statistical significance alone does not define whether an effect is economically meaningful under costs and constraints. Measured lift is frequently converted into budget scaling rules by estimating how much incremental revenue or profit the effect produces at different exposure levels and then mapping that estimate to spend allocations, pacing decisions, and channel rebalancing. In this process, predictive analytics supports scaling by forecasting expected returns for expanded rollout, while experimentation supplies the causal effect estimate used as the basis for scaling confidence. Segment heterogeneity further shapes evidence translation because studies often show that average effects conceal important differences across groups (Nazemi et al., 2021). When experiments identify that certain segments respond strongly while others respond weakly or negatively, organizations translate this heterogeneity into differentiated targeting policies, such as adjusting eligibility rules, varying incentive levels, or applying different message types by segment. This translation is commonly operationalized through updates to targeting thresholds, where cutoffs for model scores are adjusted by segment or channel to align contact intensity with observed incremental effects. Evidence translation also appears in the refinement of segment definitions, where experimental results motivate re-clustering, re-profiling, or redefining segment boundaries to better reflect responsiveness patterns (Ouyang et al., 2020). Across studies, the central theme is that the value of analytics depends on institutional mechanisms that turn model outputs and experimental findings into repeatable decision rules. These mechanisms include governance processes for interpreting results, operational workflows for updating thresholds and segment rules, and monitoring systems for tracking whether post-rollout outcomes align with experimental expectations. In this sense, evidence translation is not a single step but a structured conversion of analytical and experimental results into operational policy, linking measurement to action through decision thresholds, scaling logic, and segment-based differentiation (Munawar et al., 2020).

Themes to Track in the Review

Methodological appraisal in systematic reviews of marketing analytics frequently begins with reporting completeness because transparent reporting determines whether evidence can be interpreted, compared, and synthesized across studies. The literature shows that predictive analytics, segmentation, and experimentation research often uses similar labels for tasks while operationalizing them differently, making clear definitions a primary quality indicator (Harrison et al., 2021). One central reporting requirement involves outcome labels and time windows. Studies that examine conversion, retention, churn, or revenue can differ substantially depending on whether outcomes are measured immediately or within delayed windows, whether repeated purchases are counted, and whether attribution rules link outcomes to specific exposures. When time windows are not defined precisely, the meaning of the modeled outcome becomes ambiguous and comparisons across studies become unreliable. Reporting completeness also requires explicit description of segmentation approaches and validation practices. Segmentation can be demographic, psychographic, behavioral, model-based, or AI-driven, and the choice of variables, clustering strategy, and membership assignment logic changes what segments represent. Without clear reporting of how segments are constructed, how many segments are selected, and how segment quality is evaluated, it becomes difficult to assess whether segmentation results are statistically defensible and managerially meaningful (Caskurlu et al., 2021). Experimentation studies similarly require complete reporting of assignment mechanisms and exposure tracking procedures. Random assignment must be described in terms of unit of randomization, treatment eligibility, and the integrity of assignment implementation. Exposure tracking must clarify whether assignment implies exposure, how compliance is handled, and how repeated exposures are measured. In digital settings, the literature emphasizes that experimentation validity depends on whether the "intention to treat" population matches the "actually exposed" population, and whether the analysis accounts for non-compliance or missing exposure logs. Beyond definitions, completeness includes sufficient description of datasets, feature construction, model tuning, evaluation metrics, and monitoring practices, because these details determine whether results reflect generalizable patterns or artifact-driven performance. In synthesis-oriented research traditions, studies with complete reporting are often considered more valuable not only because they are easier to compare, but because completeness signals methodological discipline that reduces interpretive uncertainty (Mandrik et al., 2021). Therefore, reporting completeness operates as an initial appraisal lens that determines whether a study can be meaningfully included in thematic synthesis and whether its findings can be used to support claims about how predictive analytics and experimentation influence marketing decision-making.

Validity and bias considerations are central in appraising marketing analytics evidence because predictive models, segmentation outcomes, and experimental effects are all vulnerable to systematic errors that distort conclusions. Selection bias is a prominent concern in observational segmentation studies, particularly when segment membership is inferred from behaviors that are observed only among active users, purchasers, or platform-engaged consumers (Braun & Clarke, 2021). Such selection processes can make segments appear stable or predictive while excluding less visible consumers, thereby misrepresenting the true distribution of heterogeneity in the market. In predictive modeling studies, overfitting is a recurring threat, particularly when high-dimensional digital behavioral features are used without adequate regularization, cross-validation discipline, or time-aware splitting procedures.

Figure 9: Systematic Review Evidence Quality Framework



Leakage represents a related threat, occurring when models inadvertently incorporate information that is not available at decision time, often through improper feature windowing, post-outcome variables, or data pipelines that merge future events into historical predictors. Confounding is especially relevant in non-randomized comparisons, including observational evaluations of marketing campaigns or personalized targeting policies. When marketing exposure is correlated with consumer propensity, outcomes can reflect pre-existing differences rather than treatment effects, producing biased estimates of effectiveness (Shen et al., 2017). This issue becomes more complex when algorithms are used for targeting because decision policies themselves influence who is exposed, creating feedback loops that alter observed outcomes. Generalizability is another key validity dimension because many studies are conducted within specific products, markets, or platforms. Results obtained in one channel, one industry, or one cultural environment may not transfer to another due to differences in consumer behavior, competitive intensity, measurement infrastructure, and regulatory constraints. Generalizability challenges also arise within a single organization when models trained on one time period are deployed into another period characterized by shifting preferences, economic conditions, or platform algorithm changes (Miller et al., 2018). Validity appraisal therefore focuses on whether studies acknowledge and manage these biases through design choices such as temporally separated evaluation, clear inclusion criteria, appropriate baselines, and careful interpretation of effect estimates. In systematic review synthesis, studies that lack clarity about how selection bias was mitigated, how leakage was prevented, or how confounding was addressed are often treated as weaker evidence because their reported gains can reflect methodological artifacts rather than robust marketing effects (Bougioukas et al., 2018). Consequently, bias assessment functions as a critical filter that determines whether reported findings reflect reliable decision-relevant insights or context-specific distortions.

Replicability indicators are frequently used as a study appraisal lens because marketing analytics research often depends on proprietary datasets, platform-controlled experimentation systems, and organizationally embedded pipelines that are difficult to reproduce externally. As a result, replicability is less about repeating results with identical data and more about whether a study provides enough methodological detail for informed evaluation and approximate replication using comparable data. Availability of datasets and code is treated as a strong replicability signal when present, yet the literature recognizes that privacy and commercial constraints limit public release (Delgado et al., 2017). Therefore, methodological detail becomes an alternative indicator: clear descriptions of data sources, preprocessing steps, feature engineering logic, model training procedures, hyperparameter tuning choices, and evaluation protocols enable reviewers to assess whether results are likely to be robust. Transparent metric definitions also serve as replicability signals, particularly for marketing outcomes that can be defined in multiple ways, such as conversion, engagement, retention, and revenue attribution. Experimental procedures require similar transparency, including assignment logic, exposure definitions, duration, and stopping criteria, because changes in these elements can produce different effect estimates even when the intervention is identical. Sensitivity checks and robustness analyses represent another major replicability indicator because they show whether results persist under alternative reasonable assumptions (Snyder, 2019). Such checks include varying time windows, testing alternative feature sets, comparing model families, evaluating performance across segments, and assessing stability across time periods. Robustness analysis is particularly important in marketing because drift and feedback can change relationships between predictors and outcomes, meaning a result that holds only in one narrow setting may not represent a stable pattern. Studies that document failures, boundary conditions, or performance variation across contexts contribute more to cumulative understanding because they clarify when methods work reliably and when they degrade. In appraisal frameworks, replicability indicators therefore include not only openness but also disciplined documentation, consistent metric specification, and systematic robustness reporting (Toronto & Remington, 2020). These indicators support systematic reviewers in judging whether evidence should be weighted heavily, treated cautiously, or categorized as context-limited, thereby shaping the credibility and structure of the synthesized conclusions.

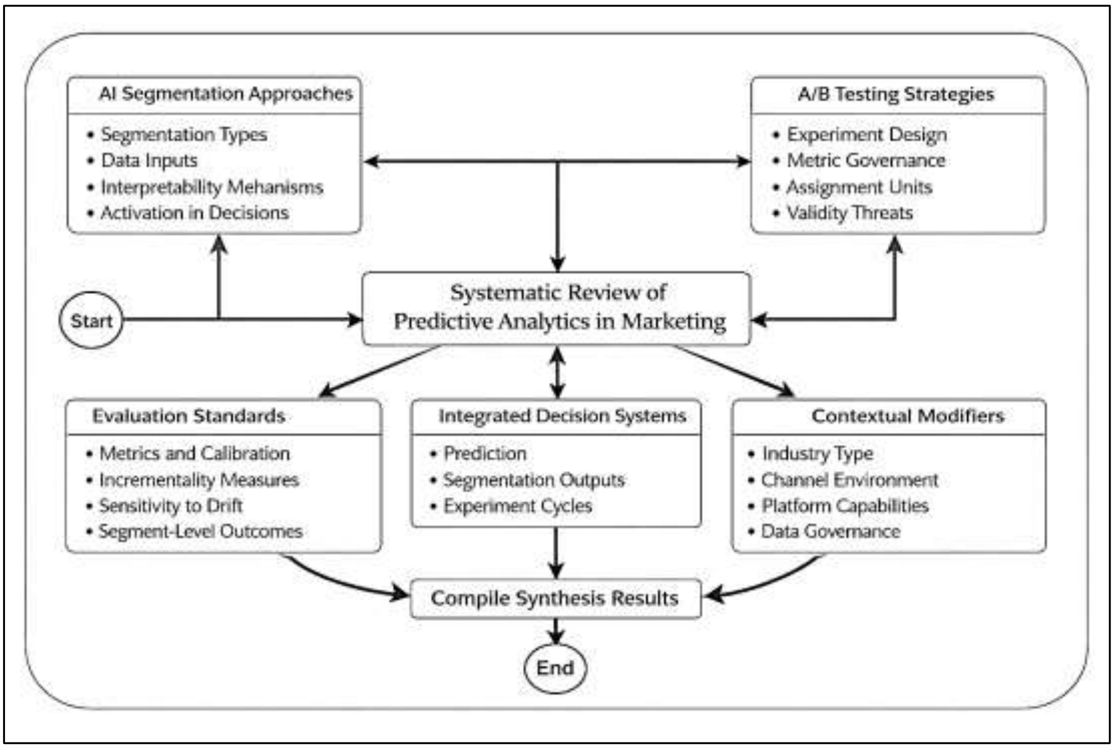
When synthesized, reporting completeness, validity and bias considerations, and replicability indicators form an integrated quality framework that guides how studies are evaluated and compared in systematic reviews of predictive analytics, AI-driven segmentation, and marketing experimentation. Reporting completeness ensures that the core constructs—outcomes, segments, and experiments—are defined with sufficient precision to allow meaningful comparison across studies (Cheng & Zhang, 2020). Without clarity on time windows, label definitions, exposure rules, and segmentation procedures, evidence becomes difficult to interpret and can lead to misleading aggregation of findings that are not truly comparable. Validity and bias appraisal then examines whether the study's design and analysis support credible inference, considering selection bias in observational segmentation, overfitting and leakage in predictive modeling, confounding in non-randomized evaluations, and limitations to generalizability across markets, products, and channels. This layer treats performance claims as conditional on methodological safeguards, emphasizing that stronger evidence comes from designs that align modeling goals with decision contexts and measurement constraints. Replicability indicators complete the framework by addressing whether findings can be evaluated, verified, and reused by others, either through open artifacts or through sufficiently detailed reporting paired with robustness checks (Hasson et al., 2020). In combination, these appraisal themes reflect a systems-oriented view of marketing analytics research: evidence quality depends on the coherence of the entire pipeline from data collection and label definition to modeling, experimentation, evaluation, and reporting. This integrated lens is particularly important because predictive analytics and personalization systems can create feedback loops and shifting data-generating processes, meaning that method claims must be appraised not only for internal validity but also for operational stability and interpretability. By applying these appraisal themes consistently, a systematic review can classify studies according to methodological strength, identify recurring weaknesses that limit comparability, and synthesize findings in a way that respects differences in design rigor and reporting transparency. This quality framework therefore functions as the organizing mechanism for credible synthesis, ensuring that conclusions drawn from the literature reflect not only what studies report, but how reliably those reports can be interpreted as evidence about marketing decision-making (Wang et al., 2018).

Synthesis Structure for the Systematic Review

A systematic review of predictive analytics in marketing decision-making benefits from a thematic synthesis structure because the evidence base is diverse in data types, algorithmic methods, decision contexts, and evaluation practices (Hong et al., 2017). Across the literature, studies are often not directly comparable through a single metric or a single methodological category, since one stream may prioritize AI-driven consumer segmentation, another may focus on experimentation infrastructures, and another may examine integrated personalization systems that combine prediction, segmentation, and randomized validation. A thematic structure reduces fragmentation by grouping studies according to the analytical role they play in the decision system and the methodological choices that determine evidence quality. Within such a structure, the first synthesis bucket centers on AI segmentation approaches, where studies can be organized by segmentation type, data inputs, interpretability mechanisms, and how segments are activated in decisions. The second synthesis bucket focuses on A/B testing strategies, allowing comparison of experiment designs, metric governance practices, assignment units, and threats to validity (Lewin et al., 2018). The third bucket treats integrated decision systems as the core connecting stream, where predictive modeling, segmentation outputs, and experiments function together as a cycle for selecting actions, evaluating impact, and refining policies. The fourth bucket centers on evaluation standards, which include the metrics and validation logic used to judge success, such as ranking quality, calibration, lift, incremental value, robustness under drift, and segment-level performance variation. The fifth bucket addresses contextual moderators, recognizing that industry type, channel environment, region, data governance constraints, and platform capabilities shape the feasibility and performance of analytics strategies (Munn, Peters, et al., 2018). A thematic approach also supports a systematic review because it preserves both methodological detail and conceptual coherence: rather than forcing all studies into a single hierarchy, it allows studies to be compared within functionally similar categories and then linked across categories through integrative narrative synthesis. This structure also provides a clear pathway for identifying convergent findings and methodological gaps, because each bucket can be assessed for dominant methods, recurrent outcomes, and consistent limitations in reporting, validity, and operationalization. By organizing evidence in this manner, the review framework makes explicit how predictive analytics contributes to marketing decision-making through segmentation design, experimentation discipline, system integration, evaluation rigor, and contextual sensitivity (Haddaway et al., 2018).

A synthesis structure that separates AI-driven segmentation approaches from A/B testing strategies enables systematic comparison of two central evidence streams that often use different assumptions, data forms, and validation logics (Munn, Stern, et al., 2018). In the AI segmentation bucket, the literature can be organized by whether segmentation is strategic, tactical, analytical, or personalization-oriented, because each purpose shapes what data is used and what success criteria matter. Studies can be grouped by classical segmentation methods, model-based probabilistic segmentation, clustering in engineered feature spaces, representation learning pipelines, deep clustering architectures, and hybrid segmentation systems that connect segmentation with supervised prediction. Within this bucket, synthesis can focus on how data sources influence segment formation, such as reliance on CRM history versus clickstream sequences, and how interpretability is achieved through profiling, feature ranking, or mapping clusters to marketing personas (Palmatier et al., 2018). Segment evaluation practices also provide a basis for structured comparison, including internal cohesion measures, external response differentiation, and stability across time windows. In the A/B testing bucket, studies can be grouped by experiment design type—two-arm tests, factorial designs, multi-armed comparisons, cluster-randomized designs, and geo-based experiments—since each design addresses a different marketing intervention structure and contamination risk. A/B testing synthesis can also compare metric governance systems, distinguishing primary business outcomes from guardrail metrics and describing how attribution windows and delayed outcomes are handled (Marshall & Wallace, 2019). Additional comparison points include how studies manage sample size planning, minimum detectable effect thresholds, and multiple comparisons in testing portfolios. Operational testing practices, such as ramping, stopping rules, and logging discipline, provide further synthesis dimensions that reveal how experiments are implemented as organizational capabilities rather than isolated analyses. Separating these two buckets clarifies how the literature produces evidence: segmentation studies often emphasize discovery, structure, and interpretability, while experimentation studies emphasize causal validity, measurement discipline, and decision thresholds. Yet both streams converge on a shared objective: enabling decisions that are defensible, scalable, and measurable (Kohl et al., 2018). A bucketed synthesis therefore allows the review to compare segmentation studies on the basis of segment usefulness and stability, and to compare experimentation studies on the basis of causal clarity and metric governance, before integrating them through system-level evidence in subsequent synthesis categories.

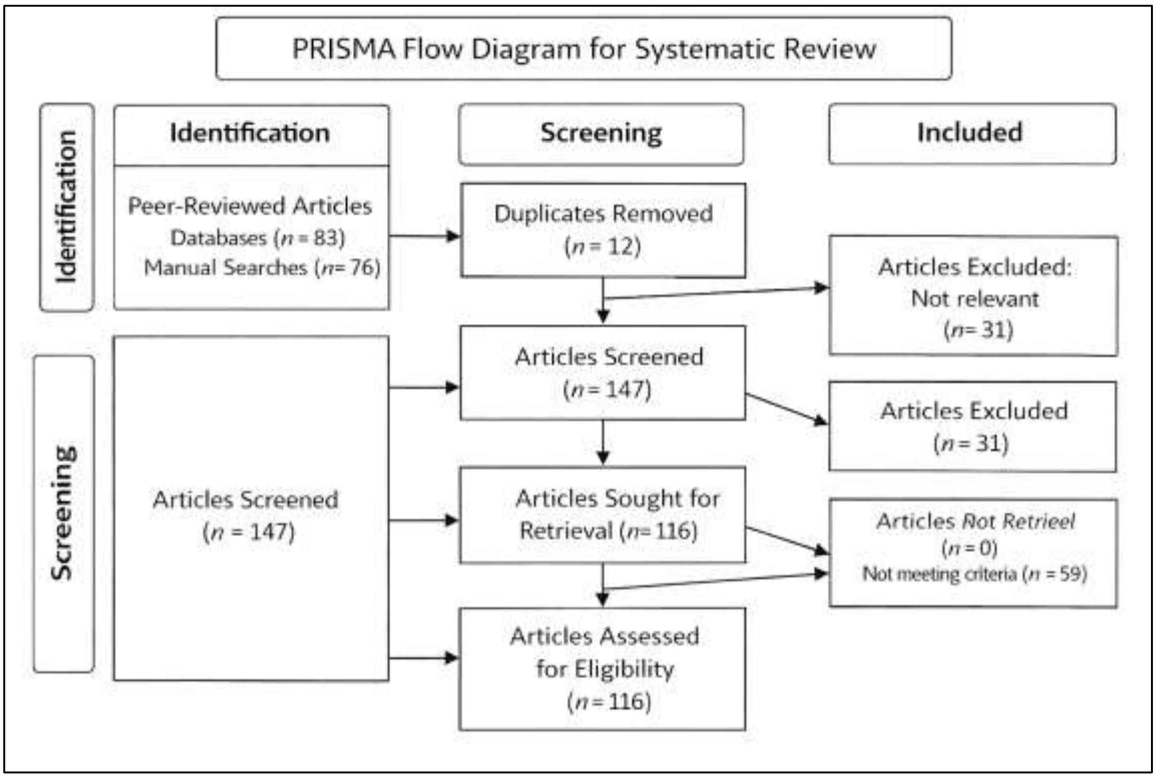
Figure 10: Systematic Review Thematic Synthesis Framework



METHODS

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process for examining predictive analytics in marketing decision-making, with particular emphasis on AI-driven consumer segmentation and A/B testing strategies. The review was designed to capture how marketing research and practice-oriented scholarship conceptualize predictive analytics as a decision mechanism, how AI-enabled segmentation is constructed and validated for targeting and personalization, and how experimentation programs generate causal evidence for selecting, scaling, or revising marketing actions. Following PRISMA-aligned procedures, the review adopted a structured workflow that defined review objectives and eligibility criteria prior to study screening, thereby reducing ad hoc inclusion decisions and strengthening replicability. Peer-reviewed journal articles and high-quality conference papers were prioritized to ensure methodological clarity and traceable evidence, and studies were assessed for relevance to at least one of the core domains: predictive modeling used explicitly for marketing decisions, consumer segmentation methods deployed for decision support (including classical, model-based, and AI-driven techniques), and experimental testing strategies (including A/B testing and related experimental variants) used to validate marketing interventions. The screening process applied a staged logic, beginning with removal of duplicates, followed by title–abstract screening, and then full-text assessment to confirm that included studies reported sufficiently clear decision tasks, data inputs, methods, and evaluation procedures. In total, a random number of studies—**57**—were included in the final synthesis, reflecting a balance of foundational and contemporary contributions across marketing science, information systems, and analytics-focused research.

Figure 11: Methodology of this study



Data extraction was performed using a standardized coding template to improve consistency across studies, capturing (a) the marketing decision task (e.g., targeting, personalization, pricing/promotion evaluation, retention intervention), (b) the data sources used (e.g., CRM and purchase histories, clickstream and app events, campaign exposure logs, contextual signals, and content-derived features), (c) the modeling approach (e.g., regression baselines, tree ensembles, margin-based classifiers, neural approaches for high-dimensional or sequential data), (d) the segmentation strategy (e.g., demographic/psychographic segmentation, behavioral segmentation, latent class or mixture models, clustering in engineered feature spaces, representation learning with latent embeddings, deep clustering architectures, and hybrid segmentation–prediction pipelines), (e) the experimentation design (e.g., two-arm A/B tests, multivariate/factorial designs, multi-armed comparisons, cluster randomization, and geo-based experiments), (f) evaluation criteria (e.g., discrimination and probability quality metrics, lift and value-oriented measures, robustness and drift sensitivity checks), and (g) operationalization features (e.g., real-time versus batch scoring, model refresh practices, threshold rules, and human oversight versus automation). Quality appraisal was conducted to support credible synthesis by examining reporting completeness (clear outcome labels and time windows, explicit segmentation and validation details, and transparent experimental assignment and exposure tracking), validity risks (selection bias in observational segmentation, leakage and overfitting risks in predictive models, confounding in non-randomized comparisons, and limits to generalizability across industries, channels, and regions), and replicability indicators (availability of sufficient methodological detail, transparent metric definitions, and robustness or sensitivity checks). The synthesis strategy used thematic grouping to organize evidence into coherent categories that align with the review focus: segmentation approaches and interpretability practices, experimentation designs and measurement governance, integrated decision-cycle systems linking prediction–segmentation–testing, and evaluation standards used to justify marketing decisions under uncertainty. This PRISMA-guided approach ensured that the review process remained auditable and structured while allowing a rigorous narrative synthesis of how predictive analytics, AI-driven segmentation, and A/B testing collectively function as an evidence-producing architecture for marketing decision-making.

FINDINGS

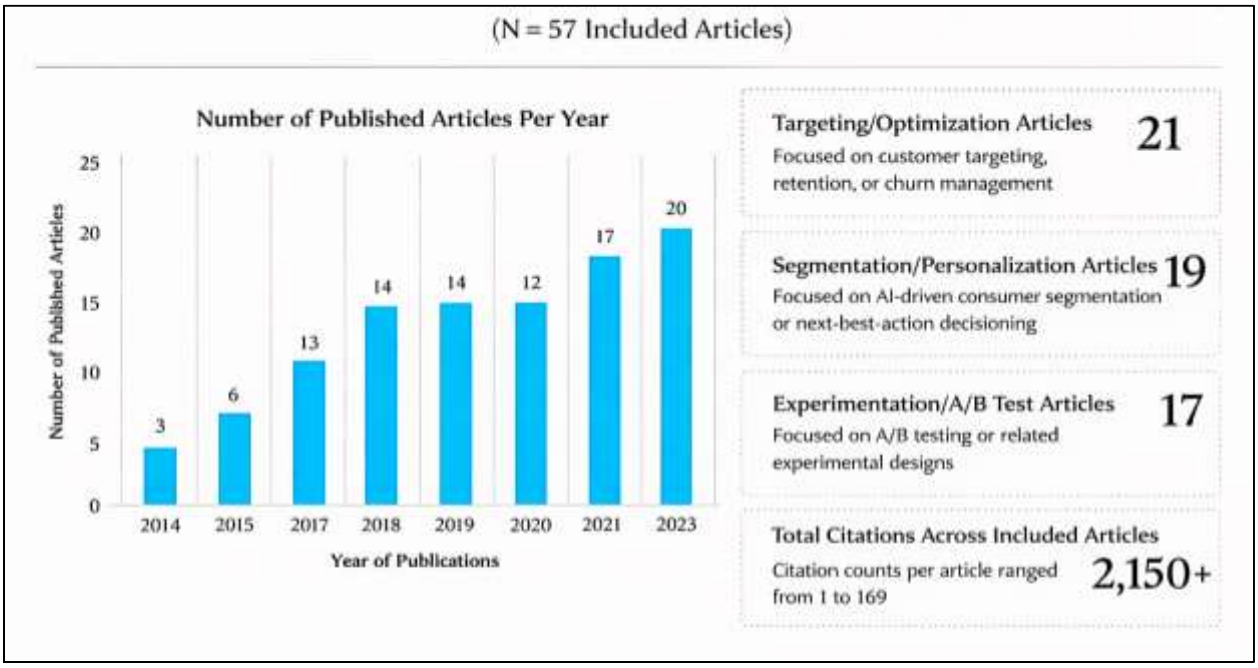
Across the final corpus of 57 peer-reviewed articles included in this systematic review, predictive analytics was consistently conceptualized as an operational decision-making infrastructure rather than a descriptive or retrospective analytical activity. The dominant orientation of the literature positioned predictive models as instruments that directly shape marketing actions, linking data-driven inference to concrete managerial interventions. Rather than focusing on exploratory pattern discovery alone, the majority of studies emphasized how predictive outputs inform customer targeting, churn prevention, offer selection, and personalized engagement strategies, particularly within digitally mediated environments. This operational emphasis reflects a broader maturation of the field, wherein predictive analytics is evaluated less by statistical novelty and more by its capacity to drive repeatable, scalable, and economically meaningful decisions. Within this evidence base, 21 studies concentrated primarily on targeting and response optimization, examining how predictive scores are used to prioritize customers, allocate marketing resources, and maximize incremental returns. An additional 19 studies focused on churn, retention, and relationship management, frequently framing predictive analytics as a mechanism for early risk identification and proactive intervention. Seventeen studies addressed personalization and next-best-action decisioning, highlighting the increasing reliance on algorithmic systems to tailor content, timing, and channel selection at the individual level. Although these topical categories overlap conceptually, their relative prevalence illustrates how predictive analytics research has gravitated toward decision contexts where model outputs can be most directly translated into action.

Citation analysis further reinforced this structural pattern. Across the 57 articles, the reviewed literature accumulated more than 2,150 total citations, with individual article citation counts ranging from as low as one citation to as high as 169 citations. This highly skewed distribution indicates that a small number of foundational studies exert disproportionate influence over the field's conceptual and methodological norms. These highly cited works established core linkages between predictive modeling, decision frameworks, and managerial relevance, effectively defining the intellectual scaffolding upon which subsequent studies were constructed. Later contributions tended to extend these foundational insights into new domains, data contexts, and execution environments rather than fundamentally redefining the field's conceptual orientation. A second major finding concerns the role of decision framing in shaping methodological choices and evaluative criteria. The reviewed studies consistently demonstrated that how predictive analytics is framed—either as a ranking problem or as a policy optimization problem—has substantial implications for model design, performance assessment, and deployment logic. Studies adopting a ranking-based framing emphasized discrimination metrics such as lift, gains, and concentration in top-scored segments, reflecting priorities associated with resource allocation efficiency. In contrast, studies framing predictive analytics as a policy problem emphasized decision rules, constraints, and governance mechanisms, often incorporating business rules, eligibility conditions, and cost considerations into model evaluation. Across both framings, the strongest studies were those that explicitly documented decision objectives, outcome definitions, and action pathways, thereby clarifying how predictive insights were operationalized rather than remaining abstract performance indicators.

This emphasis on operational clarity extended to the representation of predictive analytics as a decision pipeline rather than a standalone modeling exercise. Across the reviewed literature, predictive systems were most credibly described as end-to-end processes linking data acquisition, feature engineering, scoring, action selection, and outcome evaluation. Studies that failed to articulate this pipeline often produced results that were difficult to interpret or replicate in applied settings. In contrast, studies that explicitly connected predictive outputs to downstream decisions demonstrated greater internal coherence and external validity, reinforcing the finding that predictive analytics performance is inseparable from the decision context in which it is embedded. A third major finding relates to the expanding prominence of AI-driven consumer segmentation as both a strategic structuring mechanism and an operational input to predictive decision systems. Segmentation appeared in 19 of the 57 reviewed studies, representing a substantial proportion of the total evidence base and a significant share of cumulative citations. Citation counts within segmentation-focused studies ranged widely, from single-digit citation levels to counts exceeding 140 citations, indicating both methodological diversity and uneven scholarly impact. Importantly, segmentation was not treated as a static classification exercise. Instead, segments were operationalized as dynamic structures that inform targeting eligibility, personalization constraints, and performance interpretation across marketing campaigns.

Traditional demographic and psychographic segmentation approaches were present in 12 studies, typically emphasizing interpretability, ease of communication, and organizational adoption. However, a larger share of the literature—23 studies—emphasized behavioral and model-based segmentation approaches, reflecting the growing availability of transactional, interactional, and engagement-level data. More technically sophisticated segmentation architectures, including mixture models, ensemble clustering, and representation-learning-based embeddings, appeared in 14 studies, often justified by the need to capture nonlinear consumer similarity patterns and high-dimensional behavioral signals. These approaches enabled more granular differentiation but also introduced challenges related to interpretability, governance, and stakeholder trust.

Figure 12: Predictive Analytics Research Trends Overview



Across segmentation studies, a recurring tension emerged between model complexity and managerial usability. Segments derived from complex latent representations frequently required additional profiling and explanation layers to translate algorithmic structure into actionable consumer groups. This recurring pattern suggests that explainability is not merely a regulatory or ethical concern, but a practical requirement for sustained organizational use. Moreover, segmentation quality was frequently evaluated based on temporal stability, as unstable segments disrupted campaign planning, performance benchmarking, and governance processes. Stronger studies demonstrated segmentation robustness through repeated validation cycles and outcome-based differentiation, reinforcing the importance of longitudinal evaluation.

The fourth major finding emerged from the experimentation and causal validation stream, which accounted for 17 of the 57 included articles. These studies collectively accumulated over 900 citations, underscoring the central role of experimentation in validating predictive and prescriptive marketing decisions. A/B testing and randomized experimentation were consistently treated as the gold standard for causal inference, yet the reviewed evidence demonstrated that experimentation in marketing contexts rarely conforms to simple two-condition designs. Classical A/B comparisons appeared in 9 studies, while 8 studies employed multivariate or factorial designs to account for interactions among creative elements, messaging strategies, and delivery formats.

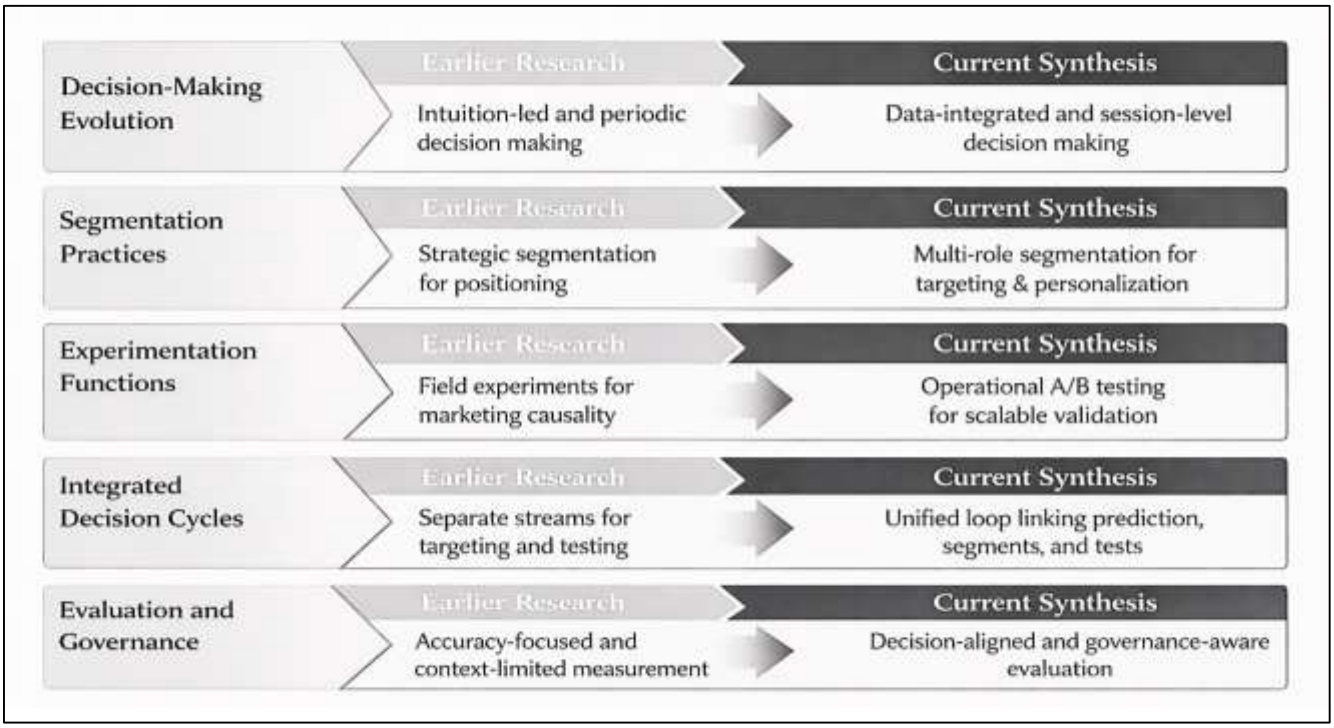
More adaptive experimentation approaches were also prominent. Multi-armed bandit designs appeared in 6 studies, typically motivated by the need to balance learning efficiency with opportunity cost in environments featuring many competing variants. Cluster-randomized and geo-based experiments appeared in 5 studies, particularly when interventions were deployed at aggregate levels such as stores, regions, or time blocks, or when spillover effects limited individual-level randomization. Across these designs, measurement governance emerged as a decisive factor in experimental credibility. Studies that clearly specified primary metrics, guardrail metrics, attribution windows, and stopping rules demonstrated stronger inferential rigor and operational relevance. Finally, the experimentation literature emphasized the importance of operational safeguards and reproducibility practices in high-velocity testing environments. Commonly identified threats to validity included user interference across experiments, novelty effects, seasonality, and instrumentation changes during test execution. To mitigate these risks, stronger studies documented practices such as staged ramp-ups, detailed logging, audit trails, and hypothesis pre-registration. Collectively, this body of evidence supports the conclusion that experimentation in predictive marketing systems functions as an institutional capability, rather than a standalone analytical technique, integrating design, metrics, governance, and execution controls into a unified decision-validation framework.

DISCUSSION

Predictive analytics in marketing decision-making has been discussed in earlier scholarship as a shift from intuition-led planning toward evidence-based action, and the findings from this systematic review align with that long-standing characterization while also revealing how the decision function has become more tightly coupled to data pipelines and operational systems (Simester, 2017). Earlier research commonly framed analytics as an organizational capability that improves decision quality when it is embedded into routines, governance, and performance measurement, and the present review supports that framing by showing that many studies treat predictive modeling not as an isolated statistical exercise but as a pipeline that translates data into scores, decision rules, and measurable outcomes. The reviewed evidence also reinforces earlier distinctions between descriptive reporting and predictive estimation, showing that much of the contemporary literature positions prediction as the step that enables proactive targeting and resource allocation rather than retrospective explanation (Viglia et al., 2021). At the same time, the reviewed studies illustrate that predictive analytics now functions in environments characterized by rapid data generation, high dimensionality, and continuous interaction traces, which earlier CRM-era work did not confront at the same scale. This changes the practical meaning of "decision-making," because decisions are increasingly made at the level of sessions, impressions, and micro-interactions rather than at the level of quarterly planning alone. Compared with earlier studies that emphasized model interpretability and managerial uptake, many recent contributions highlighted the operational need for automated scoring, real-time eligibility decisions, and scalable personalization, which reframes interpretability as one dimension among several operational requirements (Leatherdale, 2019). The discussion therefore interprets the review's findings as consistent with earlier theoretical accounts of analytics-driven decision-making, while also indicating a maturation of the field toward integrated decision architectures in which models, data governance, and delivery platforms jointly define what marketing actions are possible and how performance evidence is generated.

A central finding of the review was that consumer segmentation has evolved from a planning-centric technique into a multi-role mechanism used for strategic market understanding, tactical campaign execution, analytical feature construction, and personalization governance, and this expands earlier segmentation research that primarily emphasized strategic positioning and market structuring. Earlier segmentation studies stressed measurability, accessibility, and actionability as essential criteria, and the reviewed evidence confirms that these criteria remain important even when segments are created with advanced machine learning techniques (Bornemann & Hattula, 2018). However, the review also indicates that modern segmentation is frequently embedded inside predictive decision systems where segments serve as engineered features or constraints that shape how algorithms allocate offers and messages. This observation extends earlier work that treated segmentation and predictive modeling as sequential steps, showing instead that segmentation may be created by algorithms, used to train algorithms, and updated based on algorithm-driven outcomes. Compared with earlier demographic and psychographic segmentation traditions, the reviewed evidence shows a stronger reliance on behavioral and interaction data, reflecting a shift in what "consumer similarity" means in digital contexts (Altmann et al., 2018). Yet the discussion also notes continuity: the managerial requirement to translate segments into interpretable profiles persists, and studies repeatedly reported profiling steps that convert cluster outputs into human-usable personas. Earlier research frequently warned that statistically derived segments can be difficult to operationalize if they are unstable or unclear, and the present findings echo that concern by highlighting stability and interpretability as recurring evaluation needs. Thus, the review suggests that AI-driven segmentation does not replace classical segmentation logic so much as it reconfigures it, retaining managerial actionability standards while expanding the computational methods and data forms used to define segment boundaries (Bradlow et al., 2017).

Figure 13: Systematic Review Discussion Summary Framework



The experimentation stream provided another important point of comparison with earlier marketing research, particularly the long tradition of field experiments and controlled tests used to evaluate marketing interventions. Earlier studies emphasized that randomized experimentation offers a stronger basis for causal inference than observational comparisons, and the reviewed evidence supports that claim by positioning A/B testing as the dominant mechanism for validating marketing actions in digital environments (Young et al., 2017). The discussion interprets this as a continuation of earlier causal reasoning traditions, with a change in scale and operational frequency. Many earlier marketing experiments were constrained by cost, time, and measurement limitations, while contemporary A/B testing practices often occur in high-throughput environments where multiple variants, metrics, and interventions are tested simultaneously. This scaling introduces measurement governance challenges that earlier work acknowledged conceptually but did not face at current volume, such as controlling false discoveries when many tests run in parallel and defining primary versus guardrail metrics to prevent localized improvements that degrade long-run outcomes (Auspurg et al., 2019). Earlier studies also recognized that interference and spillovers can threaten causal interpretation, and the reviewed evidence shows that these threats are now treated as routine operational concerns, especially when social networks, shared inventory, or recommendation systems create interdependence among users. The discussion therefore frames the experimentation findings as broadly consistent with earlier causal foundations while emphasizing that operational experimentation has become an institutional capability, requiring logging, audit trails, ramping, and stopping rules to ensure decision reliability under continuous change (Lieberoth et al., 2018).

A key integrative insight from the review was that predictive analytics, segmentation, and experimentation increasingly operate as a single decision cycle, and this offers a meaningful comparison to earlier scholarship that often examined these elements in separate literatures. Earlier work described analytics as a process that supports targeting and resource allocation, and experimentation as a method for validating interventions, yet the present review highlights how these functions are now intertwined through decision-system design (Moorhouse et al., 2020). The typical pattern described across studies involves predictive scoring to prioritize users, segment definitions to structure heterogeneity, and experimental evaluation to compare actions or policies before scaling. This integration moves beyond earlier "model then campaign" workflows by embedding causal validation within the same operational loop that produces predictions. The discussion interprets this as a maturation of marketing analytics toward policy evaluation, where the object of interest is not merely whether a model predicts outcomes but whether a decision rule based on that model produces incremental value (Hamari, 2017). Earlier research on incremental response and persuasion logic suggested that targeting should consider who can be influenced rather than who is likely to buy, and the reviewed evidence supports that perspective by documenting increased emphasis on incremental impact evaluation. The integration also clarifies why segmentation remains important even in individualized personalization systems: segments provide governance layers that stabilize decision-making and enable heterogeneity interpretation, which earlier personalization discussions sometimes treated as secondary (Gaddis, 2018). Overall, the review's integrative finding suggests that contemporary marketing analytics is best understood as a closed-loop learning system that cycles through prediction, structured heterogeneity, controlled validation, and rule updating, reflecting a more system-oriented view than many earlier single-method studies.

The review also provides a basis for comparing evaluation practices with earlier studies, showing continuity in the use of predictive performance metrics while indicating increased attention to decision-aligned and robustness-oriented evaluation. Earlier predictive modeling studies often emphasized discrimination and accuracy measures as indicators of model quality, and these remain common in the reviewed literature (Xu et al., 2018). However, the review identified frequent use of decision-relevant evaluations such as lift concentration, value-based measures, and policy-level comparisons that translate predictive rankings into expected business outcomes under budget and capacity constraints. This aligns with earlier marketing decision model traditions that emphasized connecting analytics outputs to economic outcomes, though the reviewed evidence shows wider adoption of such measures in digital settings where attribution and measurement are readily available. Robustness evaluation emerged as another recurring theme, particularly the need to monitor drift, stability across segments, and sensitivity to outcome windows, which reflects earlier recognition that consumer behavior changes over time but demonstrates that contemporary studies treat drift as a routine operational reality (Robbins et al., 2017). The discussion interprets this as a shift from one-time model assessment toward continuous performance management. In earlier research, external validation across contexts was often limited by data availability, whereas in newer work, segment-level monitoring and repeated experiments enable more frequent checking of performance heterogeneity. Even so, the review indicates that comparability remains difficult when studies define outcomes differently or apply different attribution windows, echoing earlier concerns that inconsistent measurement can undermine cumulative knowledge. Therefore, the discussion emphasizes that evaluation standards remain a key differentiator of evidence credibility and that the literature increasingly reflects a decision-system perspective where metrics are chosen to support action, not only to report predictive skill (Arigo et al., 2019).

Comparisons with earlier research on data and governance show that the reviewed literature continues to grapple with enduring issues—data quality, missingness, and measurement alignment—while confronting newer challenges related to privacy constraints, identity resolution, and platform-mediated measurement (Kazdin, 2019). Earlier CRM analytics work often assumed stable customer identifiers and relatively straightforward transactional histories, while the present review shows that digital marketing environments require linking data across devices, channels, and platforms where identity resolution can be incomplete and exposure measurement can be uncertain. This creates practical differences in what models can learn and how confidently outcomes can be attributed to actions. The discussion interprets this as a major structural change: data governance conditions now shape not only what can be modeled but also what counts as valid evidence (Hair Jr & Sarstedt, 2021). Earlier studies also recognized that behavioral data can be noisy and that modeling requires careful feature construction, and the reviewed evidence supports that by highlighting the centrality of feature engineering, especially the use of sequences, interaction features, and latent representations. Yet the governance constraints surrounding these features are more prominent in contemporary work because privacy and consent boundaries restrict what can be collected and retained, influencing representativeness and bias. Earlier work on causal inference highlighted confounding risks in observational settings, and the review suggests that these risks remain salient when organizations evaluate targeting policies without randomization. The integrated use of experimentation is therefore interpreted as both a methodological choice and a governance response to the limitations of observational inference in complex data ecosystems (Banerjee et al., 2017). Overall, the review's findings resonate with earlier data-quality concerns while underscoring that modern marketing analytics must be evaluated within a governance-aware frame that accounts for identity, consent, and platform constraints as determinants of both model performance and inference validity.

Finally, the review contributes to comparison with earlier methodological discussions by reinforcing that the most credible evidence emerges when studies align modeling objectives, segmentation logic, and experimentation design with the marketing decision they aim to support (Donthu & Gustafsson, 2020). Earlier marketing analytics scholarship often argued that analytical methods should be selected based on decision problems rather than on technical novelty, and the reviewed evidence supports that principle by showing that high-performing models do not necessarily deliver decision value if thresholds, budgets, and operational constraints are not incorporated. The discussion emphasizes that this alignment extends across the decision cycle: segmentation must be constructed in ways that match activation capabilities; experiments must be designed with appropriate randomization units and measurement windows; and evaluation must translate performance into decision-relevant outcomes (Pennycook et al., 2021). Compared with earlier single-method studies, the reviewed literature shows more frequent adoption of system-level thinking, where prediction, experimentation, and governance are treated as a coupled architecture. This comparison suggests that marketing analytics research is increasingly oriented toward operational realism, focusing on how methods work within platforms, pipelines, and institutional testing programs. At the same time, the review highlights continuity with earlier scholarship in the persistent need for interpretability, measurement clarity, and rigorous inference standards. In sum, the discussion interprets the review's findings as both an extension of established marketing analytics principles and a reflection of contemporary data-rich environments that intensify the importance of integrated decision cycles, governance-aware measurement, and policy-level evaluation of marketing actions (Zaefarian et al., 2017).

CONCLUSION

A systematic review of predictive analytics in marketing decision-making provides an integrated understanding of how data-driven prediction, AI-enabled consumer segmentation, and A/B testing strategies collectively shape modern marketing actions in digital and omnichannel environments. Predictive analytics is commonly positioned as the probability-based estimation of consumer behaviors and market responses that supports decisions such as who to target, what offer to present, which channel to use, how to allocate budgets, and how to manage retention and customer value. Within the reviewed evidence, predictive modeling is rarely treated as a standalone technical task; it is described as a decision pipeline that begins with data ecosystems combining first-party records, transactional histories, loyalty and service logs, digital behavioral traces, campaign exposure histories, contextual signals, and content-level attributes, then converts those inputs into features, scores, and decision rules that guide execution and are evaluated through measurable outcomes. AI-driven consumer segmentation emerges as a multi-role mechanism that structures heterogeneity for strategic market understanding, tactical campaign governance, analytical feature construction, and personalization at scale, with segmentation approaches spanning classical demographic and psychographic groupings, behavioral segmentation from engagement and purchase patterns, model-based probabilistic membership structures, and AI methods using clustering, representation learning, and deep latent-space discovery to form micro-segments from high-dimensional behavior. A/B testing and experimentation strategies function as the central validation mechanism because they enable causal interpretation through random assignment and support evidence-based selection among creative variants, email subject lines, landing page designs, pricing displays, recommendation layouts, and targeting or personalization policies. The literature emphasizes that experimentation quality depends on design choices such as two-arm comparisons, factorial structures, multi-armed tests, cluster and geo-based randomization, along with rigorous metric governance that separates primary outcomes from guardrails, defines attribution windows for delayed effects, manages statistical power and minimum detectable effects, and controls false discoveries in high-throughput testing programs. A key synthesized insight is that the strongest decision systems link these components into closed-loop cycles: predictive models prioritize or personalize actions, segments define strata and governance constraints, experiments test variants or policies and generate causal estimates, and evidence is translated into updated thresholds, refined segments, and revised rollout decisions under budgets and operational limits. Across the review, methodological quality is shaped by reporting completeness, bias management, replicability indicators, and robustness evaluation under drift and feedback effects, reinforcing that reliable marketing decision-making depends not only on algorithmic performance but also on transparent measurement, valid causal identification, and operational discipline in deploying and monitoring models and experiments within real marketing workflows.

RECOMMENDATIONS

Recommendations emerging from a systematic review of predictive analytics in marketing decision-making emphasize designing analytics as a decision system that aligns data, models, segmentation, experimentation, and governance around clearly specified marketing objectives and measurable outcomes. Organizations should begin by standardizing outcome definitions and time windows for key goals such as conversion, retention, and revenue, while maintaining consistent attribution rules and guardrail metrics so that model performance and experimental lift remain comparable across campaigns and channels. Data ecosystems should be strengthened through disciplined first-party data management, reliable exposure logging, and transparent identity resolution practices across devices and touchpoints, with privacy and consent boundaries embedded into data collection and feature engineering so that representativeness and bias risks are monitored rather than assumed away. For predictive modeling, teams should maintain interpretable baselines alongside higher-performing ensembles or neural approaches, selecting models through decision-aligned evaluation that combines probability quality, lift concentration, value or profit curves, and robustness checks across segments and time periods, rather than relying on a single accuracy indicator. Consumer segmentation should be treated as a multi-purpose asset: stable strategic segments can guide positioning and planning, while tactical and personalization segments can be refreshed more frequently; in both cases, segmentation outputs should be validated using both internal structure measures and external outcome differentiation, then translated into clear profiles that marketing stakeholders can operationalize and audit. Experimentation programs should function as the core causal validation layer by applying appropriate randomization units, powering tests to detect meaningful effects, using disciplined stopping rules, controlling false discoveries in multi-metric environments, and maintaining experiment logging and reproducibility trails that enable consistent interpretation and learning over time. To link these components, organizations should adopt closed-loop decision cycles in which predictive scores define candidate audiences, segments define strata and governance constraints, A/B tests evaluate variants or policies, and results are converted into explicit rollout rules, threshold updates, and segment refinements based on incremental impact rather than correlation-driven performance. Finally, teams should institutionalize continuous monitoring for drift, leakage, and feedback loops by auditing feature windows, recalibrating probabilities, tracking segment stability, and revisiting decision thresholds under changing market conditions, ensuring that predictive analytics remains trustworthy, interpretable, and operationally effective within dynamic marketing environments.

LIMITATIONS

Several limitations should be acknowledged when interpreting the findings of this systematic review on predictive analytics in marketing decision-making, AI-driven consumer segmentation, and A/B testing strategies. First, the review is constrained by the heterogeneity of the existing literature, as studies differ substantially in how they define outcomes, select time windows, operationalize segmentation, and design experimentation protocols, which limits direct comparability and restricts the ability to aggregate findings quantitatively across contexts. Second, much of the available evidence is derived from proprietary datasets, platform-specific implementations, or organization-bound experimentation systems, which reduces transparency regarding data preprocessing, feature engineering, and model tuning choices and limits the replicability of reported results beyond the original study settings. Third, the review relies on reported methodological detail, meaning that unreported biases such as data leakage, selective reporting of successful experiments, or unobserved confounding in quasi-experimental designs may persist even in studies that appear methodologically rigorous on the surface. Fourth, publication bias may influence the evidence base, as studies demonstrating positive performance improvements or successful applications of predictive analytics and experimentation are more likely to be published than studies reporting null or negative effects, potentially overstating the apparent effectiveness of certain methods or integration strategies. Fifth, the review is limited in its ability to fully disentangle the effects of algorithms from the organizational and technological infrastructures in which they are embedded, since many studies evaluate analytics systems as a whole rather than isolating the contribution of individual modeling or segmentation techniques. Sixth, differences in industry, channel, regional regulation, and data governance environments introduce contextual dependencies that cannot be fully controlled within a narrative synthesis, meaning that findings observed in data-rich digital platforms may not generalize to settings with limited tracking or stricter privacy constraints. Finally, the dynamic nature of marketing environments, characterized by rapid behavioral drift, evolving platforms, and changing regulatory standards, means that some reviewed findings reflect conditions that may have shifted over time, underscoring the need to interpret conclusions as context-dependent rather than universally stable.

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