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AI-Driven Customer Behavior Modeling for Performance-Based Digital Marketing Systems

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Abstract

This study addresses a practical problem in performance-based digital marketing: organizations increasingly deploy AI models to predict and influence customer behavior, yet reported improvements in conversion efficiency and ROI are inconsistent because data signals, activation decisions, and measurement logic vary widely across cloud marketing stacks and enterprise platforms. The purpose of this research is to quantify, compare, and explain what AI-driven customer behavior modeling approaches work best, under what data conditions, and with which evaluation designs, using a quantitative cross-sectional, case-based synthesis. The sample comprises N = 45 peer-reviewed cloud and enterprise cases (2005–2023) drawn from marketing systems implemented across contexts such as e-commerce conversion optimization, subscription and SaaS retention, mobile funnels, and omnichannel operations. Key variables include AI technique family (supervised ML, deep learning or sequence models, recommenders, causal or uplift models, bandits or reinforcement learning), signal strategy (RFM and value features, clickstream and session features, exposure intensity, context and creative features, multi-source integration), activation lever (targeting, bidding and budget allocation, creative selection, timing and frequency control, lifecycle messaging), and measurement approach (observational attribution vs quasi-experimental incrementality vs experimental lift tests). The analysis plan applies descriptive frequency statistics, structured vote-counting of KPI direction, and a 5-point Likert evidence-support scoring to test hypotheses about performance lift, multi-source advantage, incrementality alignment, and governance effects. Headline findings show supervised ML as the most prevalent technique (31/45, 68.9%), while deep learning or sequence models appear in 19/45 (42.2%) and causal or uplift modeling in 12/45 (26.7%); overall, 33/45 studies (73.3%) report positive KPI movement attributable to AI-informed modeling, with H1 receiving strong support (M = 4.08, SD = 0.71). Multi-source data integration demonstrates stronger consistency, with 17/20 (85.0%) multi-source studies reporting positive impact versus 16/25 (64.0%) single-source studies, supporting H2 (M = 3.89, SD = 0.77). Measurement rigor is the most decisive moderator: incrementality-oriented studies report positive conclusions 24/27 (88.9%) versus 9/18 (50.0%) for attribution-only studies, yielding the strongest hypothesis support for H3 (M = 4.22, SD = 0.64). Finally, governance-explicit cases show more stable gains (15/18, 83.3%) than governance-implicit cases (18/27, 66.7%), supporting H4 (M = 3.76, SD = 0.80). These results imply that enterprises should prioritize consent-aware multi-source signal integration, operationalize model outputs into clear activation levers, and validate impact through incrementality-based measurement to avoid optimizing toward credited but non-incremental outcomes.

Keywords

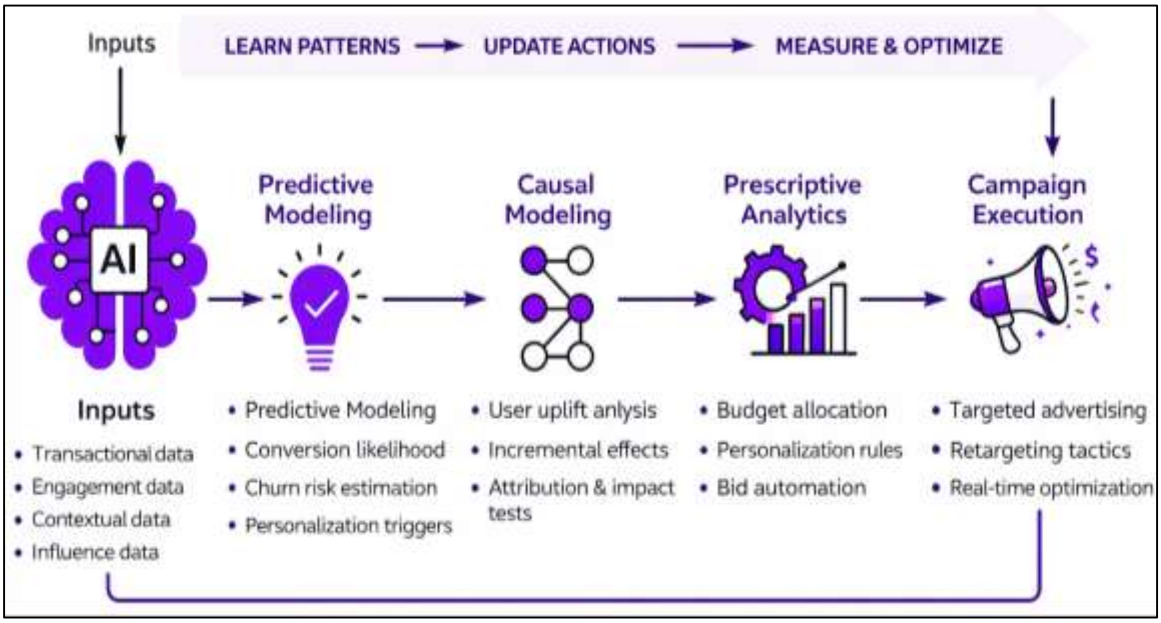
AI-Driven Customer Behavior Modeling; Performance-Based Digital Marketing; Incrementality Measurement; Multi-Source Data Integration; Uplift and Causal Modeling;

INTRODUCTION

Artificial intelligence (AI) in marketing is commonly defined as the use of machine-based computational techniques that learn patterns from data to support or automate decisions related to customer targeting, personalization, and performance measurement, with "AI-driven" systems typically combining predictive modeling with data pipelines and decision rules that adapt marketing actions in near real time (Adomavicius & Tuzhilin, 2005). In digital marketing, "customer behavior modeling" denotes the analytical representation of consumers' observable actions—such as browsing, clicking, searching, purchasing, and sharing—so that firms can estimate propensities, elasticities, and causal responses to marketing stimuli. A performance-based digital marketing system refers to an operational setup where spend allocation and campaign management are continuously evaluated against measurable outcomes (e.g., conversions, revenue, customer lifetime value), often through programmatic delivery and algorithmic optimization loops (Aral et al., 2013). These definitions matter internationally because digital marketing infrastructures now sit at the intersection of global platform ecosystems, cross-border data flows, and multinational competition, where firms in diverse markets rely on standardized measurement constructs and platform-mediated auctions to reach audiences and to justify investments (Li et al., 2010). The global scaling of customer analytics has expanded the strategic importance of data-rich environments in which firms integrate structured transaction logs with unstructured and semi-structured signals such as text reviews, social media interactions, and streaming engagement traces. As a result, AI-driven modeling is increasingly treated as a managerial capability that supports customer journey governance across channels and devices, enabling the coordination of messaging, offers, and timing across touchpoints that are geographically distributed and platform dependent. International significance also derives from the fact that marketing performance systems influence resource allocation decisions in both large and small organizations, and these decisions often hinge on measurement validity, attribution logic, and the reliability of behavioral predictions (Li & Kannan, 2014). In that context, AI-driven customer behavior modeling is not simply an analytical exercise; it is embedded in organizational routines that convert behavioral data into campaign actions and business reporting, creating a continuous link between consumer signals and operational outcomes (Devriendt et al., 2018). Scholarly treatments of algorithmic marketing emphasize that value is produced through the alignment of data capture, model estimation, and decision execution, which together form a socio-technical system whose performance depends on both technical accuracy and managerial interpretation (Lewis & Rao, 2015).

Digital customer behavior occurs across a journey composed of multiple stages and touchpoints, including awareness, consideration, purchase, and post-purchase engagement, and research shows that understanding this journey requires connecting interactions that occur across channels and platforms into an integrated analytic view (Ashley & Tuten, 2015). Customer behavior modeling in performance-based marketing typically begins with observational logs—impressions, clicks, dwell time, add-to-cart actions, and purchases—then expands to include engagement and influence signals that occur in social and community environments, where consumer-to-consumer communication affects demand and brand perception (Babić Rosario et al., 2016). Electronic word-of-mouth (eWOM) has been synthesized as a measurable influence driver with systematic links to sales outcomes, with meta-analytic evidence showing that platform characteristics, product conditions, and metric choices moderate the strength of observed relationships. In parallel, customer engagement research has emphasized that firm performance is tied not only to immediate conversion events but also to engagement behaviors and relational outcomes captured in digital traces (Lambrecht & Tucker, 2013). Within this setting, marketing analytics is frequently described as operating in "data-rich environments," where the abundance of signals is accompanied by heterogeneity in data quality, missingness, privacy constraints, and platform-level measurement limits, which jointly shape what models can reliably infer (Kushwaha & Shankar, 2013; Mosheur & Rebeka, 2021). A key implication for customer behavior modeling is that the "behavior" being modeled is often a composite of platform-defined events, firm-defined KPIs, and consumer-defined actions, which must be reconciled through feature engineering and measurement design to produce stable and interpretable predictors. Marketing scholarship has also highlighted that digital marketing spans paid, owned, and earned media, where outcomes are shaped by both firm-controlled messaging and consumer-controlled content circulation. This has motivated analytic designs that incorporate sequential exposure histories and cross-touchpoint dependencies so that marketing actions can be linked to subsequent behavior in a way that supports performance evaluation (Faysal & Shamsunnahar, 2022; Verhoef et al., 2007). The operational importance of journey-based modeling is amplified in performance marketing because optimization requires feedback loops: estimates of what drives incremental conversions must flow into budget allocation rules, bidding strategies, and creative selection processes (Habibullah & Zaheda, 2022; Trusov et al., 2009). At the same time, measurement research demonstrates that apparent performance can be misleading when experiments are underpowered or when variance in outcomes is high, which places increased emphasis on robust evaluation logic and cautious interpretation of model-driven lift estimates (Zhang et al., 2018).

Figure 1: Conceptual Framework of AI-Driven Customer Behavior Modeling in Performance-Based Digital Marketing Systems



AI-driven customer behavior modeling for performance-based marketing is commonly organized around predictive, causal, and prescriptive analytic families. Predictive models estimate propensities such as conversion likelihood, churn risk, or responsiveness, often using classification, regression, or sequential modeling over high-dimensional features derived from digital traces. Research has shown that marketing problems such as churn prediction can be formulated as supervised learning tasks were featuring construction and algorithm selection influence stability and business usefulness (Bleier & Eisenbeiss, 2015; Siddique & Amin, 2022; Md & Islam, 2022). In performance marketing contexts, predictive scores are frequently used to rank audiences, trigger personalization rules, and prioritize retargeting exposures, creating a direct line from model output to campaign execution. Causal modeling, in contrast, aims to estimate incremental effects—what would change under a marketing action relative to a counterfactual—because performance-based optimization seeks evidence of incrementality rather than correlation. Uplift modeling is central in this space because it explicitly targets individual-level treatment effects, enabling marketers to allocate interventions where incremental gains are largest (Du et al., 2019; Mosheur & Rebeka, 2022; Mostafa & Tohidul, 2022). Benchmarking work on multitreatment uplift modeling shows that practical settings often involve multiple action alternatives, requiring evaluation approaches that reflect business objectives and constraints rather than solely predictive accuracy (Devriendt et al., 2020; Ara, 2023; Jinnat & Rakib, 2023). Prescriptive analytics extends causal and predictive insights into decision rules that maximize profit or value under constraints, which aligns closely with performance marketing's budget-limited allocation problems (Lemon & Verhoef, 2016; Khaled & Mosheur, 2023; Shahab & Aditya, 2023). In many platform environments, allocation occurs through auctions and programmatic pipelines where the system must choose which user to target, with what creative, at what time, and at what price, linking behavioral prediction to operational control. Real-time bidding (RTB) research frames display advertising delivery as an algorithmic decision process in which the expected value of an impression is estimated and then converted into a bid, connecting user-level behavior modeling with marketplace dynamics. Attribution modeling occupies a bridging role because it transforms exposure histories into credit assignment rules that influence future budgets, campaign continuation, and optimization policy updates (Kumar & Ravi, 2013; Hasan Or et al., 2023; Mehedi & Nahar, 2023). Multi-touch attribution (MTA) work has advanced sequential and recurrent modeling approaches combined with principled credit allocation methods, including Shapley-based logic, to more directly connect sequences of exposures to conversion outcomes. Across these strands, the conceptual center of AI-driven customer behavior modeling for performance marketing is the engineered connection between data signals, model estimates, and the decision loop that updates marketing actions (Goldfarb & Tucker, 2011; Sultan & Anick, 2023; Mostafa, 2023).

Behavioral data signals in digital marketing are typically grouped into transactional events, engagement interactions, contextual attributes, and network or social influence indicators. Transactional events include purchase histories, basket composition, and subscription states, which are often used to estimate value-related metrics such as customer lifetime value (CLV) and to support segmentation that prioritizes retention and growth (Fader et al., 2005; Ratul & Aditya, 2023; Zaheda & Farabe, 2023). CLV-oriented customer analytics emphasizes that long-run value depends on repeat purchase dynamics and the ability to forecast future transactions from observed frequency and recency patterns. Engagement interactions include clicks, dwell time, scrolling depth, email opens, and social reactions, which serve as intermediate signals that may precede purchases and can be used for early detection of interest shifts in performance campaigns (Efat Ara, 2024a, 2024b; Neslin et al., 2006). Content analyses of branded social content demonstrate that creative strategies and channel contexts are associated with different engagement outcomes, supporting the role of creative-feature engineering as part of behavior modeling in social and performance settings (Iftekhar & Tohidul, 2024; Jinnat & Binte, 2024; Ma & Sun, 2020). Contextual attributes include device type, geography, time-of-day, and referral source, and these features influence both baseline conversion rates and responsiveness to advertising, motivating interaction features that combine user, context, and message characteristics. Retargeting effectiveness research indicates that ad information specificity and the structure of the message can shape response, highlighting that feature engineering must capture not only user history but also message design and the match between product, consumer state, and channel (Rendle, 2010). Social influence indicators include review volume and valence, sharing cascades, and peer-generated exposure, where empirical evidence supports a measurable association between word-of-mouth and sales outcomes under identifiable moderators (Towhidul & Uddin, 2024; Mushfequr & Aditya, 2024; Rust & Huang, 2021). In performance marketing systems, feature engineering operationalizes these signals into numerical representations, such as counts, recency-weighted aggregates, sequence encodings, and latent factors derived from high-dimensional sparse interactions. Factorization machine formulations have been adopted as a practical approach for learning interactions among sparse categorical variables, which is relevant to advertising and recommendation settings where user-item-context combinations are numerous (Sazzadul & Rebeka, 2024; Tasnim & Anick, 2024; Xu et al., 2014). At the platform level, additional signals arise from auction dynamics and delivery constraints, where bid landscapes and pacing behavior can distort observed exposure patterns, shaping what the data represent and how models should be interpreted. The challenge for AI-driven behavior modeling is therefore not simply the availability of data but the disciplined transformation of heterogeneous signals into features whose meaning aligns with marketing constructs and whose measurement limitations are acknowledged in the analytic design (Zhang et al., 2014).

A theoretical foundation is needed to connect observed digital behaviors to psychological and contextual mechanisms that explain how marketing stimuli translate into responses. One widely used lens in digital environments is the stimulus–organism–response (SOR) tradition as applied to online settings, where marketing stimuli (e.g., ad content, personalization cues, platform design) are interpreted as inputs that shape internal states such as affect, trust, and perceived relevance, which then influence behavioral responses such as click-through, purchase, and sharing (Kannan & Li, 2017). Empirical work applying SOR-oriented perspectives in online contexts has shown that environmental cues and perceived value can shape internal evaluations that are linked to online purchasing behavior, supporting the relevance of organism-level constructs for modeling digital response (Kannan et al., 2016). In performance-based marketing systems, this theoretical grounding is practically consequential because many AI models rely on behavioral proxies (e.g., clicks) that may represent different underlying states across contexts, requiring careful attention to construct validity and interpretation. Trust and privacy considerations are central in the organism layer because consumer reactions to tracking and personalization can mediate how marketing actions influence behavior, and privacy regulation research has shown that restrictions can change the effectiveness of targeting mechanisms in measurable ways (Gubela & Lessmann, 2021; Shahab, 2025; Zaheda & Hamidur, 2024). Studies of privacy regulation and online advertising have demonstrated that limits on data collection can reduce targeting effectiveness, indicating that governance conditions influence both the data available for modeling and the behavioral response to marketing actions (He et al., 2017). Research on programmatic advertising and consumer concerns suggests that perceptions of surveillance, intrusiveness, and transparency affect attitudes and behavioral outcomes, which links governance and ethics directly to performance outcomes rather than treating them as separate managerial topics (Huang & Rust, 2021; Mostafa, 2025; Sazzadul, 2025). This connection is reinforced by marketing scholarship that emphasizes the need to align analytic practices with customer relationship objectives, as performance systems often influence customer experience through repeated exposure, retargeting intensity, and message timing decisions (Samuel & Booth, 2021). From a theory-guided modeling standpoint, the practical value of SOR alignment is that it encourages explicit mapping between stimulus features (creative, context, frequency), organism proxies (engagement quality, sentiment, trust signals), and response outcomes (conversion, retention), supporting a coherent interpretation layer for AI-driven decision loops (Santini et al., 2020; Shamsunnahar, 2025; Yousuf et al., 2025). It also highlights that ethical and governance design becomes part of the analytic system because privacy constraints, consent boundaries, and fairness expectations shape which stimuli are permissible and which data signals are legitimate inputs for behavior modeling. In this way, theory is integrated into the operational logic of performance-based systems by clarifying the psychological and contextual pathways through which algorithmic actions may influence observed behavior (Wedel & Kannan, 2016).

Performance-based marketing requires measurement systems that translate behavioral data into credible estimates of impact, yet marketing science and econometric evidence shows that measuring returns to advertising can be statistically difficult even in large-scale settings. Field-experiment evidence indicates that uncertainty in ROI estimates can remain large and that confidence intervals can be wide, which constrains the certainty with which marketers can claim incremental effects (Shao & Li, 2011). This measurement difficulty is amplified when multiple channels and repeated exposures create correlated histories, leading organizations to rely on attribution methods that assign conversion credit across touchpoints. Multi-touch attribution has been formulated as a structured approach to credit assignment in which exposure sequences are modeled and then decomposed into contribution shares, so that budgets and bids can be updated in line with estimated influence (Shankar et al., 2016). Research on data-driven attribution has emphasized that modeling choices in the response function and in credit allocation rule design can meaningfully change inferred channel value, which is particularly important when performance systems automate decisions based on these inferred values. Sequential deep-learning–oriented attribution frameworks have been proposed to better represent dependence patterns in exposure sequences and to support incremental attribution logic using credit allocation mechanisms such as Shapley-based decomposition, linking sequence modeling with a principled allocation concept (Shankar, 2018). At the same time, auction-based delivery systems create selection effects because ad exposure is not random; it depends on bids, predicted value, and platform constraints, which makes causal identification challenging when relying on observational data alone. Consequently, uplift modeling and treatment-effect estimation approaches have been positioned as alternatives or complements to standard response modeling because they directly target incremental effects under treatment/control logic. Empirical and methodological work has shown that evaluation metrics aligned with business value can outperform purely treatment-effect ranking policies by integrating expected value and incremental response into decision rules (Aral et al., 2013). These measurement and evaluation concerns are not separable from AI modeling because performance systems often use measured lift and attributed outcomes to retrain models, tune bids, and adjust segmentation rules, forming feedback loops that can magnify measurement error if governance and evaluation design are weak. Marketing analytics scholarship therefore treats attribution and experimentation as structural components of performance-based systems, shaping how customer behavior modeling is validated, compared, and operationalized rather than treating models as isolated prediction engines (Kumar & Ravi, 2013).

Implementation of AI-driven customer behavior modeling in performance marketing involves technical, organizational, and governance challenges that can determine success or failure. From a technical standpoint, modern performance marketing relies on integrating multi-source data pipelines, resolving identities across devices, handling missingness and delayed conversions, and maintaining feature stores that preserve consistent definitions of behavioral signals over time (Lambrecht & Tucker, 2013). Algorithmic effectiveness also depends on how models represent sparse, high-dimensional interactions among users, ads, contexts, and products, which motivates the use of interaction-learning approaches such as factorization machines in settings where categorical combinations explode. Programmatic execution adds complexity because optimization decisions are mediated through RTB auctions and platform policies, where bid strategies must reflect both estimated conversion value and marketplace dynamics (Lewis & Rao, 2015). Organizationally, performance-based systems require alignment between marketing objectives, analytics teams, and platform operations, with clear definitions of success metrics and documented assumptions about attribution, incrementality, and KPI reporting. Research on AI and customer analytics has also emphasized that value creation depends on managerial understanding of what models do and how model outputs map to decision authority, supporting the view of AI as a collaborative capability rather than a purely autonomous mechanism (Samuel & Booth, 2021). In marketing applications, accountability concerns include transparency of targeting logic, fairness in segmentation outcomes, compliance with privacy expectations, and robustness against drift and platform measurement changes, which collectively shape stakeholder trust in the system. Governance challenges are practically linked to performance because privacy and transparency conditions influence both what data can be collected and how consumers interpret personalization, affecting response behavior and long-run relationship outcomes. Additionally, evaluation research suggests that profit-oriented metrics and value-driven evaluation methods can alter targeting decisions and improve economic outcomes, emphasizing that implementation is not solely about model accuracy but about aligning evaluation, decision rules, and business value definitions (Verhoef et al., 2007). In sum, AI-driven customer behavior modeling for performance-based digital marketing systems is implemented as an end-to-end managerial system where behavioral signals are engineered into features, models translate features into estimates, and estimates are embedded in optimization loops that update marketing actions under measurement constraints and governance boundaries (Kannan et al., 2016).

This study is structured around three interlinked objectives that collectively define its analytical scope and guide the organization of the review. The first objective is to identify and systematize the dominant AI techniques used to model customer behavior within performance-based digital marketing systems, with particular attention to how these techniques are positioned across common marketing tasks such as conversion propensity prediction, churn risk identification, customer lifetime value estimation, audience segmentation, personalization, and sequential journey modeling. Achieving this objective requires distinguishing between predictive modeling approaches that estimate the likelihood of outcomes, causal and uplift-oriented approaches that seek to quantify incremental impact, and prescriptive approaches that translate model outputs into actionable optimization rules. The second objective is to synthesize the behavioral data signals and feature-engineering strategies that underpin successful modeling outcomes in performance-based environments. This includes examining how studies represent customer journeys through event-based logs, how they encode recency, frequency, intensity, and sequence patterns, and how they integrate multi-source inputs such as transactional histories, engagement traces, contextual attributes, and creative characteristics into unified representations that support reliable learning and decision use. This objective also emphasizes clarity in the operational definitions of marketing KPIs and behavioral constructs, ensuring that modeled "behavior" is consistently linked to measurable business outcomes. The third objective is to evaluate how AI-driven behavior models are embedded into performance marketing decision loops and assessed through measurement frameworks, focusing on the alignment between optimization actions and evaluation logic. Under this objective, the review examines how model outputs inform targeting, bidding, pacing, and creative selection, and how impact is quantified through attribution and incrementality approaches that aim to assign credit across touchpoints and channels. Alongside these three core objectives, the study also aims to consolidate implementation insights through a case-study lens, organizing evidence around practical deployment conditions such as data availability, channel context, governance boundaries, monitoring requirements, and ethical constraints that shape real-world performance. By pursuing these objectives in a coordinated way, the study builds a coherent evidence map linking techniques, signals, decision integration, and measurement practices to observed marketing performance outcomes, producing a structured foundation for consistent comparison across studies and contexts.

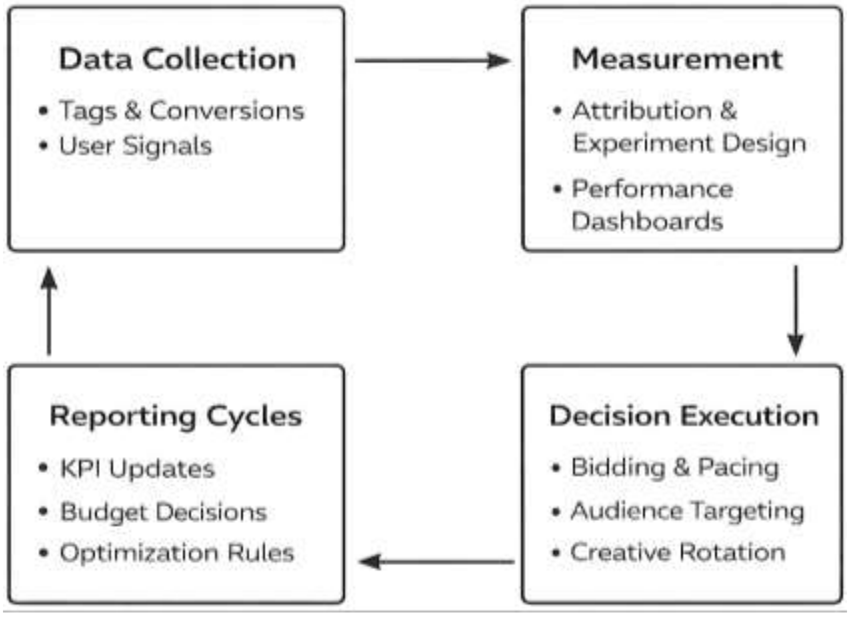
LITERATURE REVIEW

The literature review has established the conceptual and empirical foundation for examining how AI-driven customer behavior modeling has supported performance-based digital marketing systems by integrating insights from performance measurement, customer analytics, data governance, artificial intelligence, and attribution research. Performance-based digital marketing has been structured around measurable outcomes such as conversions, revenue, return on ad spend, cost per acquisition, retention, and customer lifetime value, and it has operated through continuous monitoring and optimization cycles that have translated metrics into concrete actions such as targeting adjustments, bid allocation, creative refinement, and sequencing strategies. Within this environment, customer behavior modeling has functioned as the analytical bridge between raw digital traces and managerial decision-making, transforming heterogeneous interaction data—clickstreams, transactional histories, exposure logs, and contextual signals—into interpretable customer states that have represented intent, value, engagement, or churn risk. As omnichannel journeys have become more fragmented and dynamic, the literature has emphasized the importance of integrated data ecosystems, consistent event definitions, identity resolution processes, and governance frameworks to ensure that model outputs have remained reliable and aligned with business objectives. AI and machine learning techniques have been adopted to scale prediction, detect non-linear relationships, encode sequential patterns, and support personalization at granular levels; however, prior scholarship has consistently suggested that algorithmic sophistication alone has not guaranteed superior performance. Instead, value creation has depended on whether model outputs have been embedded into actionable decision loops and evaluated through credible measurement standards that have distinguished true incremental impact from correlation-based attribution. The review has also drawn on theoretical perspectives that have interpreted digital marketing systems as structured stimulus–organism–response processes, where marketing cues and platform conditions have acted as stimuli, inferred customer states have represented organismic mechanisms, and measurable KPIs have constituted responses that have fed back into future optimization. This integrated perspective has justified a structured synthesis approach that has mapped modeling techniques, signal categories, activation levers, measurement designs, and governance constraints into a coherent analytical framework. Consequently, the literature review has positioned AI-driven customer behavior modeling not as a standalone predictive tool but as a socio-technical system whose effectiveness has depended on the alignment of data quality, theoretical grounding, operational decision rules, and incrementality-aware evaluation standards within performance-based digital marketing environments.

Performance-Based Digital Marketing Systems and KPI Logic

Performance-based digital marketing systems can be defined as organizational and platform-enabled arrangements in which advertising and communication activities are planned, executed, and continually adjusted according to observable outcomes that are quantified as key performance indicators (KPIs). In this logic, "performance" is operationalized through measurable customer actions—such as qualified site visits, leads, purchases, repeat purchases, subscriptions, and revenue—that are linked to spending decisions through reporting cycles and automated optimization routines. The system perspective is essential because performance marketing is not a single campaign tactic; it is a coordinated set of components that includes data collection (tagging, events, conversions), measurement (attribution rules, experiment design, dashboards), and decision execution (bidding, pacing, targeting, creative rotation). In computer-mediated environments, the marketing function increasingly operates through digital intermediaries and platform rules, which shapes what can be measured and how quickly decisions can be updated across channels, markets, and devices (Yadav & Pavlou, 2014). For firms operating internationally, the "performance-based" approach provides a common managerial language for comparing outcomes across regions, product lines, and channel mixes, but it also requires careful KPI definitions to ensure that a click, lead, or conversion represents comparable business value across contexts. In practice, performance systems decompose goals into hierarchical KPI structures: business outcomes (profit, revenue, retention) are supported by value proxies (customer lifetime value, average order value) and behavior proxies (click-through rate, add-to-cart rate, time on site). The managerial challenge is to align these layers so that short-horizon indicators drive actions that are consistent with longer-horizon value outcomes, while avoiding metric fragmentation across teams, platforms, and agencies. This alignment problem explains why modern performance marketing frequently relies on standardized KPI dictionaries, automated reporting, and decision workflows that translate KPI deltas into concrete actions such as reallocating spend, refining audiences, or changing creative. This framing clarifies how models are judged by KPIs.

Figure 2: Performance-Based Digital Marketing Systems and KPI Logic Framework



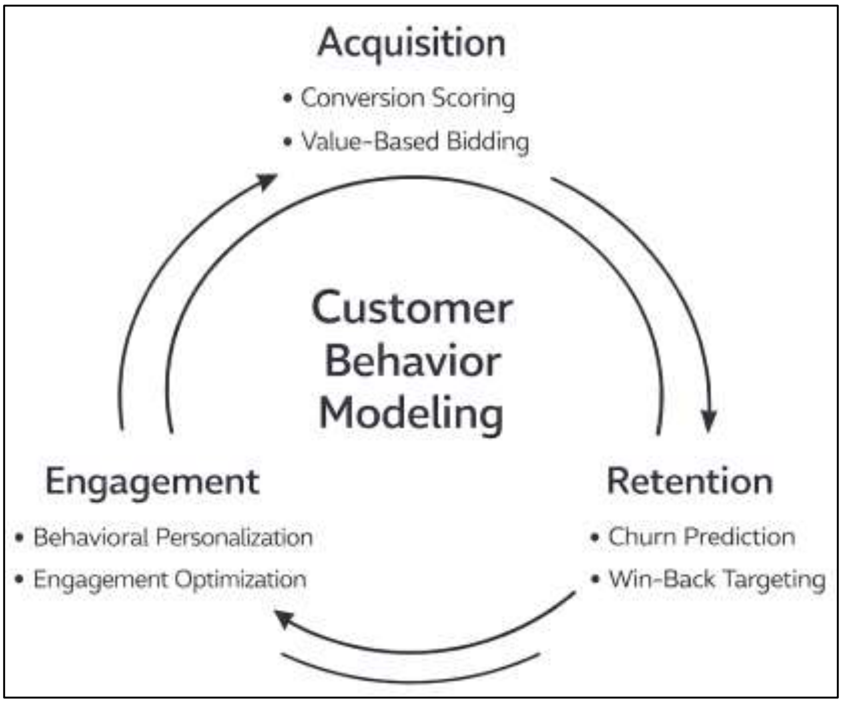
KPI logic in performance-based systems is most effective when it is embedded in a marketing performance measurement system that specifies what is measured, how frequently it is evaluated, who uses the metrics, and how metrics influence resource allocation decisions. Research on marketing performance measurement emphasizes that comprehensiveness alone does not guarantee better outcomes; rather, the usefulness of metrics depends on whether they support alignment, learning, and decision quality under the organization's strategic complexity (Homburg et al., 2012). In digital marketing, this requirement appears as the need to separate operational KPIs (impressions, reach, frequency, clicks) from effectiveness KPIs (conversions, incremental lift, contribution margin) and to establish explicit causal assumptions about how operational activity translates into effectiveness outcomes. A key implication for performance-based systems is that KPI selection must reflect both the customer journey stage and the controllability of the metric: upstream metrics are often faster and cheaper to observe, while downstream metrics are closer to business value but noisier and slower to mature. Web analytics functions as a measurement backbone by collecting and organizing behavioral traces into interpretable aggregates that can be used for diagnosis and optimization. Evidence from digital marketing performance measurement shows that firms extract value from web analytics not merely by adopting tools, but by choosing the right metrics, processing them into decision-ready summaries, and embedding them into organizational routines for learning and action (Järvinen & Karjaluoto, 2015). Accordingly, KPI logic in performance marketing is both technical and managerial: it requires consistent event definitions, robust data governance, and a shared interpretation framework that connects KPI movement to plausible behavioral explanations (e.g., a drop in conversion rate linked to page speed, audience mismatch, or creative fatigue). For cross-sectional case studies, KPI hierarchies help compare campaigns at a single time point, while preserving contextual notes about channel mix and objectives.

Because performance-based systems are designed to justify spending through measurable outcomes, accountability and reporting architecture become central features of the KPI design. A performance assessment process typically includes (1) specifying objectives and success criteria, (2) selecting metrics that represent those objectives, (3) collecting and analyzing data, (4) disseminating insights to decision makers, and (5) using metrics to update resource allocation and operational tactics. Contemporary scholarship highlights that these stages are increasingly shaped by marketing automation, cross-market operations, and integrated customer experience management, which makes metric choices consequential for both governance and competitive positioning (Morgan et al., 2022). Within digital marketing, a KPI logic often centers on profitability and efficiency ratios—such as return on ad spend (ROAS), cost per acquisition (CPA), and customer acquisition cost (CAC)—but these ratios depend on denominator and numerator definitions, attribution windows, and conversion qualification rules. KPI frameworks therefore require explicit documentation of measurement boundaries (what counts as a conversion), temporal rules (when credit is assigned), and comparability rules (how metrics change across platforms or regions). Systematic KPI overviews in web analytics emphasize that organizations benefit from classifying indicators into quantitative and qualitative groups and linking them to the "why" and "how" of user interaction, rather than relying on isolated counts that do not guide action (Saura et al., 2017). In performance marketing operations, this classification supports dashboard design, where leading indicators (traffic quality, engagement depth) are monitored to anticipate lagging indicators (revenue, retention). It also supports cross-functional coordination by enabling finance, marketing, and analytics teams to reconcile short-term efficiency metrics with longer-term value metrics. In sum, KPI logic is the rule set that converts customer behavior data into interpretable signals and then into budget and execution decisions; its quality determines whether performance-based digital marketing systems produce coherent, comparable, and action-relevant assessments across campaigns, channels, and markets.

Customer Behavior Modeling and Marketing Use Cases

Customer behavior modeling in digital marketing refers to the structured representation of how individuals and segments move through observable actions—exposure, attention, search, evaluation, purchase, and post-purchase activity—so that firms can quantify value creation and choose interventions that improve outcomes. In performance-based systems, the model is expected to connect micro-behaviors (views, clicks, cart events, repeat visits) to macro-KPIs (revenue, ROAS, CAC, LTV), which makes the definition of "behavior" inseparable from the definition of value. A central goal is therefore to translate noisy behavioral traces into stable customer states (e.g., high intent, price sensitivity, loyalty, exploration) that can be acted on through targeting, bidding, creative selection, and lifecycle messaging. Literature on customer lifetime value (CLV) and customer equity positions behavior modeling as a resource-allocation tool: customer histories are summarized into purchase propensities and retention patterns, then used to prioritize acquisition, retention, and expansion programs under budget constraints (Gupta et al., 2006). Within this view, segmentation is not only demographic; it is behavioral and economic, separating customers by expected future contribution, responsiveness, and risk. Performance marketing use cases commonly include conversion propensity scoring for acquisition, next-best-offer selection for cross-sell, and value-based bidding where predicted margin and probability of purchase jointly determine spend levels. Journey-oriented modeling extends these use cases by recognizing that conversions often arise from sequences of touches, meaning that behavior models must encode recency, frequency, sequence order, and channel context to provide decision-ready signals. Cross-sectional synthesis helps compare how these constructs are operationalized across industries and channels, while a case-based lens clarifies how context shapes model choice. As a result, customer behavior modeling becomes a bridge between measurement and execution: it defines the unit of optimization (individual, cohort, segment), the objective function (efficiency, profit, value), and the time horizon (immediate conversion vs. long-term relationship outcomes) that performance systems attempt to maximize.

Figure 3: Customer Behavior Modeling Goals and Core Marketing Use Cases in Performance-Based Systems



A second set of goals focuses on preventing value erosion by identifying customers likely to disengage or churn and determining which retention actions can change that trajectory. Churn modeling is widely treated as an applied predictive task where the objective is to rank customers by exit risk using subscription status variables, usage patterns, and customer–firm interaction signals; this ranking support offers, service recovery, and outreach in performance programs that emphasize retention ROI. Evidence from subscription settings shows that machine-learning approaches such as support vector machines can improve churn prediction accuracy, and that parameter selection and feature design materially influence operational usefulness (Coussement & Poel, 2008). These designs frequently incorporate service contacts, complaint logs, and migration signals. However, the managerial purpose of churn models is not only to identify risk but to allocate interventions efficiently; performance marketing systems must distinguish between customers who are high risk and customers who are sensitive to the intervention being offered. Work on proactive retention demonstrates that targeting the highest-risk customers can be inefficient when those customers are the least responsive to marketing actions, highlighting the need to incorporate treatment responsiveness (lift) into retention decisioning rather than relying on risk alone (Ascarza, 2018). This distinction reframes customer behavior modeling from prediction to decision support: the best model is the one that improves incremental outcomes under constraints, not necessarily the one that best predicts churn labels. In performance-based digital marketing systems, retention use cases therefore include uplift-aware targeting for win-back campaigns, cadence optimization for lifecycle messaging, and value-based prioritization that balances expected future value against intervention cost. When these components are integrated, retention models become part of the same closed loop as acquisition models, with shared KPI logic that compares the marginal benefit of acquiring a new customer versus retaining or expanding an existing one.

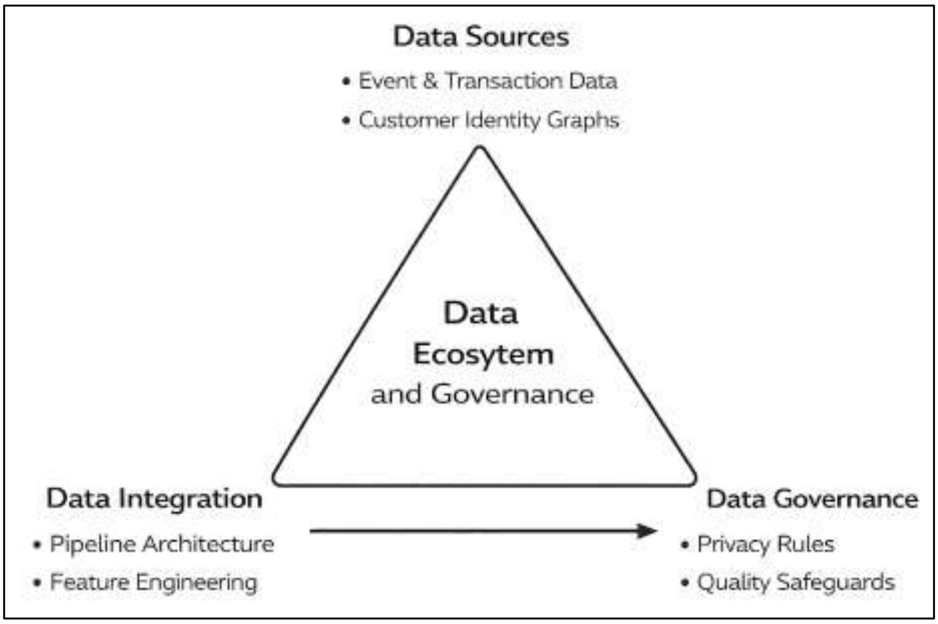
A third cluster of objectives emphasizes engagement and personalization as mechanisms that shape both short-term response and longer-term relationship strength. Engagement is commonly conceptualized as customers' cognitive, emotional, and behavioral investment in interactions with a brand or platform, expressed through repeated participation, attention, contribution, and advocacy behaviors that can be captured as digital traces and organized into measurable constructs for marketing decisioning (Brodie et al., 2011). In performance marketing, engagement signals often function as leading indicators that guide creative iteration, audience refinement, and message sequencing before downstream conversion is observed, which is especially important when conversion cycles are long or multi-stage. Engagement can also be operationalized through metrics—such as view-through depth, repeat sessions, and share behavior—that support diagnostics of relevance. Personalization is then positioned as an action layer that uses behavior models to tailor content, offers, and timing to inferred customer states, aiming to improve relevance and efficiency. Yet personalization uses cases operate under a dual requirement: extracting informational value from data while maintaining consumer trust. Evidence shows that information collection strategies can increase ad effectiveness when paired with trust-building mechanisms, and that the same personalization intensity can produce different outcomes depending on whether consumers interpret data use as helpful or intrusive (Aguirre et al., 2015). This relationship makes governance a behavioral variable: privacy cues, transparency, and perceived control shape the organism-level states that mediate response, so effective behavior models must consider not only what customers do but how they interpret the marketing environment. In practice, these considerations influence frequency caps, sequencing rules, and optimization objectives that balance efficiency with relationship quality. Across acquisition, retention, and engagement, customer behavior modeling thus serves a unifying role in performance-based systems by aligning data signals, customer states, and action policies with KPI definitions that can be monitored and improved across campaigns and channels.

Data Ecosystem and Governance for AI-Driven Behavior Modeling

Customer behavior modeling in performance-based digital marketing depends on a data ecosystem that can capture, integrate, and activate heterogeneous signals at scale. In practice, the ecosystem includes data sources (web/app events, ad exposures, transactions, CRM records, call-center logs, and third-party enrichments), data movement (tagging, APIs, streaming pipelines), and data structures (identity graphs, feature stores, and KPI tables) that keep model inputs consistent with business definitions. Big-data consumer analytics research emphasizes that value is created when organizations can (a) collect and store evidence of consumer activity with sufficient volume, velocity, and variety, (b) extract actionable insight through analytics, and (c) embed that insight into adaptive capabilities that change marketing actions in response to observed behavior (Erevelles et al., 2016). For performance marketing systems, this means the data layer must be engineered to support rapid feedback: campaign exposures must be joined to downstream behaviors, and those behaviors must be mapped to KPIs that are meaningful for budget allocation and optimization. The ecosystem therefore requires standardized event taxonomies, conversion definitions, and windowing rules so that model training data and evaluation reports represent the same behavioral constructs. It also requires lineage and metadata documentation so analysts can interpret whether a feature represents consumer intent, platform delivery constraints, or measurement artifacts. When these foundations are weak, models may appear accurate while encoding unstable proxies, producing optimizations that shift spending without producing durable KPI gains. A case-based review perspective highlights that data architecture choices vary by industry and platform dependency, yet the core requirement remains the same: behavior models are only as reliable as the completeness, consistency, and interpretability of the behavioral traces that feed them, consistently. In cross-sectional comparisons, studies repeatedly show that differences in tagging discipline, identity stitching, and conversion validation can materially change which customers appear “high value” and which channels appear “efficient.”

Because a large share of performance marketing is executed through digital platforms, the data ecosystem is also governed by platform rules that determine what can be observed, shared, and optimized. Platform data strategy scholarship frames these rules as choices about data access, data sharing, and accountability across stakeholders, including users, advertisers, and regulators (Bhargava et al., 2020). For AI-driven customer behavior modeling, these matters because the same behavioral event can carry different meaning depending on how a platform defines it, how it is attributed, and whether it is available at user level, cohort level, or only in aggregated reports. As platforms limit cross-site identifiers and constrain third-party tracking, organizations are pushed toward first-party data infrastructures where customer data is collected directly and then linked across touchpoints using identifiers. This shift increases governance decisions about identity resolution, data minimization, retention policies, and access control, since these policies determine which features can be used in modeling and how frequently the feature space can be refreshed. Marketing privacy research synthesizes how privacy functions as a psychological construct, an economic boundary, and a societal governance constraint, implying that performance systems must treat privacy compliance and consumer expectations as structural conditions and not peripheral considerations (Martin & Murphy, 2017).

Figure 4: Data Ecosystem and Governance Foundations For AI-Driven Customer Behavior Modeling



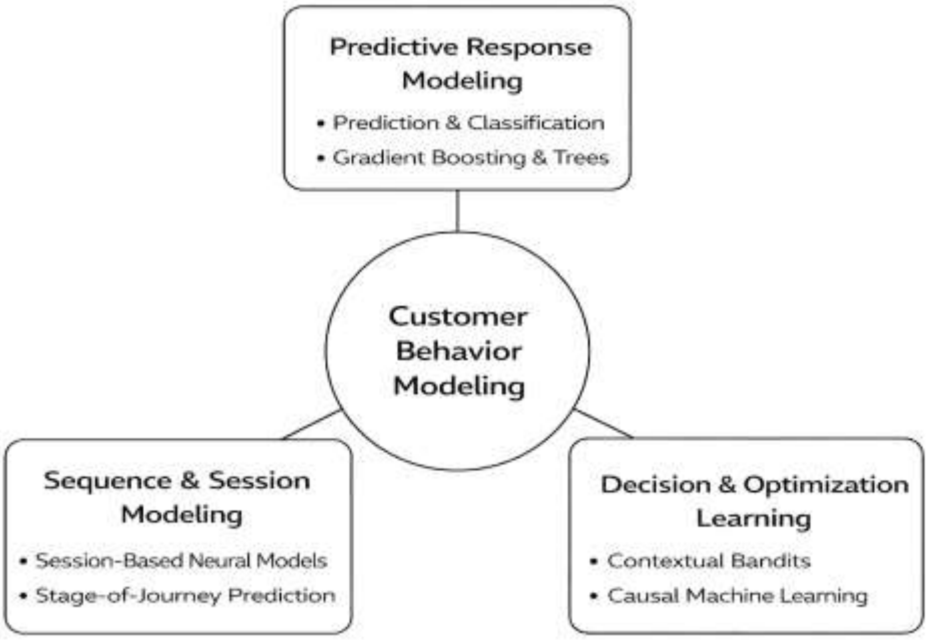
For performance-based optimization, governance becomes operational: teams must specify what constitutes permissible personalization, how sensitive attributes are handled, and how transparency and choice mechanisms are implemented within journeys. In case-study contexts, firms that formalize data dictionaries, consent flags, and audit trails tend to report more stable KPI baselines, because measurement logic is less likely to drift when vendor settings change or when campaign structures evolve. As a result, the data ecosystem is best viewed as a socio-technical contract that aligns platform constraints, organizational policies, and analytic requirements into a coherent environment for model training and decision execution. The effectiveness of AI-driven customer behavior modeling is shaped by organizational analytics capability and by the quality of the digital trace data that the ecosystem produces. Capability-oriented research on big data analytics argues that performance gains depend on more than tool adoption; firms need aligned strategy, managerial commitment, and routinized processes for translating data into coordinated action (Akter et al., 2016). In performance marketing, these routines include monitoring data freshness, managing feature drift, validating conversion pipelines, and reconciling discrepancies between platform-reported outcomes and internal transaction records. Digital trace data are typically “uncontrolled” in the sense that they are generated by operational systems, platform interfaces, and user-device contexts, which introduces missingness, duplication, bot noise, and measurement discontinuities that can undermine model reliability if not explicitly assessed. Work on trace-data quality highlights that researchers and practitioners must evaluate and report issues such as representativeness, consistency, and transformation steps, because these hidden decisions affect statistical power and replicability of findings derived from traces (Vial, 2019). For performance-based systems, this translates into practical safeguards: documenting feature construction, versioning datasets and models, and stress-testing KPIs under alternative attribution windows or event definitions. It also suggests that “accuracy” should be interpreted alongside data-quality diagnostics, since a model trained on biased traces may optimize toward artifacts like delivery constraints or measurement gaps. In cross-sectional, literature-review synthesis, these points support a structured coding of studies by (1) data provenance (first-party, platform-reported, or fused), (2) identity linkage method, (3) feature governance and privacy handling, and (4) quality validation practices. When combined with case evidence, such coding clarifies why similar algorithms can yield divergent marketing outcomes across contexts: differences in data capability and trace quality often dominate algorithm choice.

AI/ML Techniques for Customer Behavior Modeling

AI/ML techniques used for customer behavior modeling in performance-based digital marketing systems can be organized into three functional layers: (a) predictive response modeling for estimating propensities such as click, conversion, churn, or purchase probability; (b) representation and interaction learning for encoding user–item–context relationships and high-dimensional sparse marketing data; and (c) decision and optimization learning for selecting actions that maximize KPI-defined rewards under budget and delivery constraints. In many applied marketing settings, predictive response modeling remains the workhorse because performance systems require fast scoring of large audiences and stable ranking signals to support targeting and bidding. Tree-based gradient boosting methods are widely used for these tasks due to their ability to handle non-linearities, mixed feature types, and missing values while delivering competitive accuracy and operational speed, making them suitable for structured marketing datasets derived from event logs and CRM tables (Chen & Guestrin, 2016). From a behavior-modeling standpoint, these models are often paired with engineered features capturing recency, frequency, intensity, and channel interaction effects to predict near-term conversion likelihood and to generate actionable segments. Alongside boosting models, the literature increasingly treats digital marketing data as inherently sparse and interaction-heavy, where the outcome depends on combinations of user state, context, creative, and timing. This has strengthened interest in representation learning techniques that reduce dimensionality and preserve local structure in high-dimensional behavioral feature spaces, supporting improved segmentation, audience discovery, and feature construction for downstream predictive models (McInnes et al., 2018). When framed in performance-based KPI logic, these predictive and representational techniques are valued not only for accuracy but for their capacity to produce robust, repeatable signals that can be monitored across campaigns and compared across channels at a single cross-sectional point. As such, the “best” predictive approach is often the one that balances interpretability, training stability, and computational efficiency, enabling marketing teams to translate model output into operational decisions such as retargeting thresholds, exclusion rules, or budget shifts without destabilizing KPI reporting cycles.

A second family of techniques focuses on sequence and session modeling, reflecting the fact that digital customer behavior frequently unfolds as temporally ordered events rather than independent clicks. In performance marketing contexts, customers may encounter multiple exposures, browse multiple pages, compare products, abandon carts, and return through different entry points, creating sequences that encode intent progression and decision readiness. Session-based neural methods are designed to learn from such ordered interaction streams and to forecast next actions or next items by modeling dependencies within sessions, enabling improved personalization and more responsive triggering of marketing interventions (Hidasi et al., 2016)). For customer behavior modeling, the importance of sequence learning lies in its ability to encode short-term intent and context shifts, which can matter more than static customer attributes in fast-moving auction and retargeting environments. In applied performance systems, sequence models can be used to infer stage-of-journey states (e.g., exploration vs. evaluation vs. purchase intent), to rank products or offers likely to convert within the current session, and to identify moments where the marginal probability of conversion is highest. This aligns with performance-based use cases such as dynamic creative selection, personalized landing experiences, and event-triggered messaging, all of which depend on accurate detection of “now” intent rather than long-run averages. At the same time, session and sequence modeling introduces methodological and operational requirements: consistent event ordering, stable sessionization rules, and careful handling of sparsity and cold-start behaviors, because many customers exhibit short or incomplete trails. Within a literature-review synthesis, the technique choice is therefore evaluated through its compatibility with available signals, the stability of KPI-linked outcomes, and its practicality in environments where model updates must occur without disrupting measurement baselines or campaign operations.

Figure 5: Functional AI And Machine Learning Layers Supporting Performance-Based Behavior Modeling

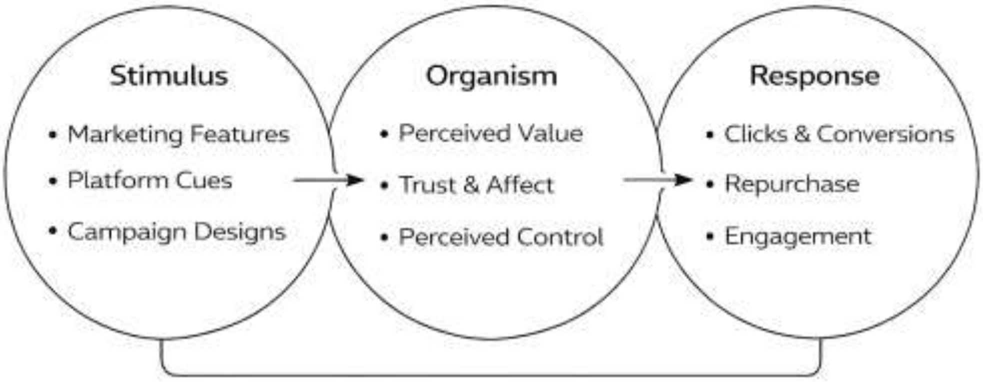


A third cluster of techniques connects behavior modeling to **decision optimization** by learning policies that select marketing actions—such as which content to show, which offer to send, or which impression to bid on—based on context and expected reward. Contextual bandit approaches are frequently used in these settings because they formalize a balance between learning (exploration) and performance (exploitation) while optimizing measurable outcomes such as click or conversion, which maps naturally to performance-based KPI objectives (Chapelle & Li, 2011). For customer behavior modeling, this shifts the analytical focus from predicting outcomes to choosing interventions that change outcomes, making the modeling problem inherently causal and value-oriented. In this space, causal machine learning provides tools for estimating heterogeneous treatment effects, supporting action selection by identifying customers whose behavior is most likely to change under a marketing intervention rather than those who are merely likely to convert anyway. Causal forest methods, for example, estimate treatment-effect heterogeneity using flexible nonparametric learning, offering a pathway to uplift-aware targeting and more credible incrementality logic in performance systems (Wager & Athey, 2018). This decision-oriented perspective aligns with performance marketing's managerial requirement to justify spend by incremental impact rather than by correlated response, and it connects directly to measurement frameworks where attribution and experimentation aim to validate lift. In practice, organizations may integrate predictive scoring for scale, sequence learning for timing and relevance, and bandit/causal approaches for policy selection, producing hybrid systems where customer behavior models serve both as predictors and as components of adaptive optimization loops. In literature synthesis, these techniques can be compared by the decision problem they solve (ranking vs. sequencing vs. policy learning), the KPI they optimize, and the governance requirements they impose.

Stimulus–Organism–Response for AI-Driven Performance Marketing

Customer behavior modeling in performance-based digital marketing systems can be theoretically anchored in the Stimulus–Organism–Response (S–O–R) paradigm, which explains how environmental inputs shape internal evaluations that subsequently drive observable actions. For this study, "stimuli" are treated as measurable marketing and platform cues engineered from campaign logs and interaction data, including message framing, personalization intensity, frequency, timing, interface quality, and incentive design. "Organism" refers to intervening psychological and cognitive states that translate stimuli into action, operationalized in digital settings through constructs such as perceived value, trust, affect, perceived control, and involvement, which are often measured using validated scales and then linked to behavioral outcomes. "Response" denotes behavioral endpoints used in performance marketing, such as click-through, conversion, repurchase intention, recommendation, and engagement behaviors.

Figure 6: Theoretical S–O–R Model for Customer Behavior in Performance-Based Digital Marketing



A meta-analytic consolidation of S–O–R findings in retail environments supports the generalizability of the S–O and O–R linkages and highlights the centrality of organismic states—especially affective components—in explaining approach-type behaviors, justifying organism variables as more than descriptive attitudes (Vieira, 2013). In online contexts, S–O–R applications show how web and platform stimuli influence attitudes, emotional regulation, and repurchase intentions, aligning with performance marketing that attempts to increase measurable responses by tuning controllable cues (Peng & Kim, 2014). Social commerce evidence further indicates that design-related stimuli (e.g., information and service quality) shape perceived value, and perceived value then drives loyalty-related intentions such as repurchase and recommendation, illustrating a mediating pathway compatible with KPI systems that track both immediate and longer-horizon outcomes (Molinillo et al., 2021). In this study, the S–O–R lens functions as the organizing theory connecting AI-driven signal extraction (stimuli features) to customer-state inference (organism) and to performance endpoints (response), allowing the literature review to code findings consistently across contexts and model types. This framing is suited to cross-sectional case comparisons because stimuli, organism states, and KPI responses remain comparable.

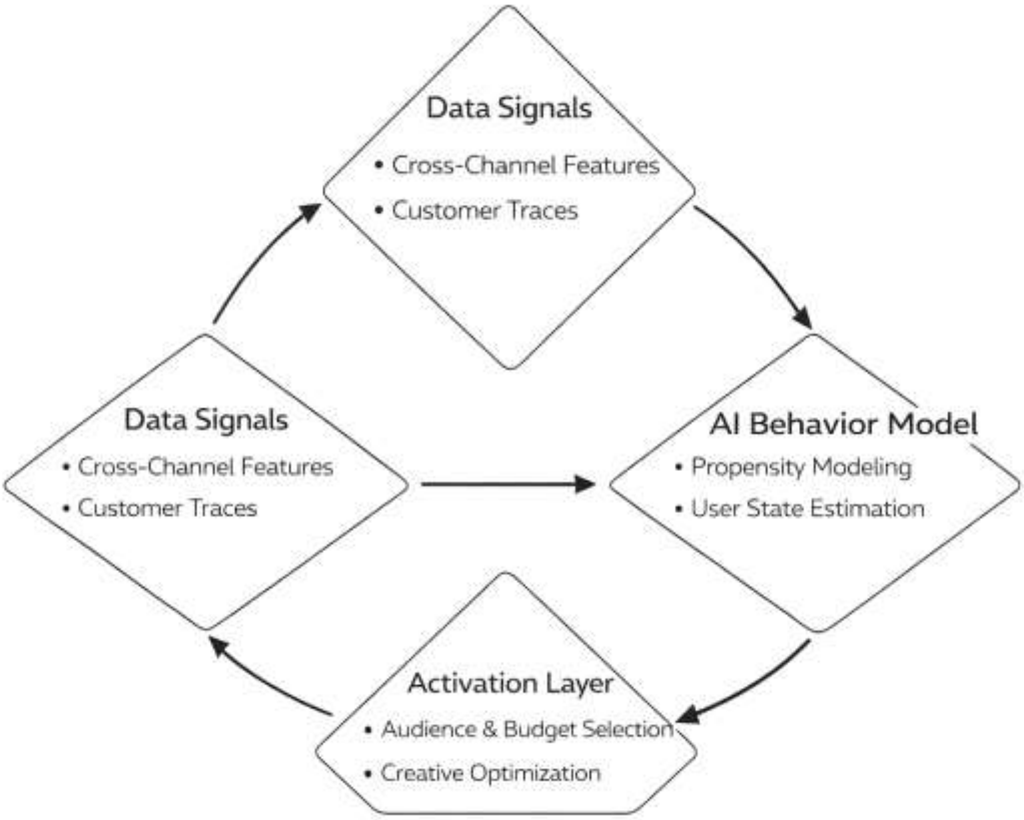
To make the framework analytically usable for a literature-review and case-oriented synthesis, the S–O–R relationships are expressed in a compact structural form that can be applied as a common coding template across studies. Let S be a vector of stimulus features from the marketing environment (e.g., personalization, interactivity, rewards, information quality, exposure frequency), O be a latent or composite organism score (e.g., trust, perceived value, affect), and R be a KPI-aligned response (e.g., conversion, engagement, repurchase intention). The mediation structure can be written as: $O = \alpha_0 + \alpha^{T}S + \varepsilon$_O and $R^* = \beta_0 + \beta_1 O + \beta^{T}S + \varepsilon$_R, where R* is response tendency. If R is binary (conversion), then $P(R = 1 \mid S, O) = 1 / (1 + e$^{-($\beta_0 + \beta_1 O + \beta^{T}S$)}). This representation separates the direct effect of stimuli on response (β^{T}) from the indirect pathway ($\alpha^{T} \times \beta_1$), matching performance marketing where a cue may lift clicks while changing trust or value perceptions. Online brand community evidence shows community characteristics acting as stimuli that shape engagement as an organismic state and then influence loyalty outcomes, reinforcing the mediation logic captured in the equations (Ul Islam & Rahman, 2017). Brand community research in social media similarly applies S–O–R to show how participation motivations (stimuli) influence trust/loyalty-related internal states (organism) that drive co-creation behaviors (response), supporting the use of a mediation-form template for organizing results across digital contexts (Kamboj et al., 2018). In this review, these equations function as the "best" formula set because they map onto most empirical findings while remaining faithful to the theory that internal states transmit marketing effects into measurable action. When studies report standardized path coefficients or odds ratios, they can be translated into comparable evidence of α and β parameters, enabling a numeric synthesis within a qualitative review.

Using this theoretical template, the review will code each included study by (1) the stimulus class it manipulates or observes, (2) the organism variables it measures or infers, and (3) the response metrics used to claim "performance." Stimuli will be grouped into controllable marketing levers (personalization, creative framing, incentives, frequency, channel mix) and platform or interface levers (information quality, interactivity, service quality, friction, transparency cues). Organism variables will be treated as the mechanism layer that explains why the same stimulus can produce different outcomes across segments and cases, which is essential for customer behavior modeling because AI models often learn latent states that resemble perceived relevance, trust, and value even when these constructs are not measured directly. Responses will be aligned with performance-based decision logic by distinguishing immediate reactions (click, add-to-cart), conversion endpoints (purchase, subscription), and relationship endpoints (repeat purchase, recommendation, engagement). The equations introduced above provide a consistent interpretation rule for the numeric portion of the findings section: whenever a study reports the magnitude of a stimulus-to-response effect, the review will classify it as a direct effect ($\boldsymbol{\beta}^{\mathrm{T}}$) or as an indirect, organism-mediated effect ($\boldsymbol{\alpha}^{\mathrm{T}} \times \boldsymbol{\beta}_{1}$), and then summarize direction and relative strength using descriptive tallies (e.g., count of positive, negative, and null links per stimulus category). This approach supports a qualitative, cross-sectional, case-study synthesis because it preserves contextual explanations (industry, channel, audience, data type) while enabling an evidence map of which stimuli reliably shift organism states and which organism states predict KPI responses. It also creates a bridge to the paper's AI focus: model features and engineered signals are treated as observable proxies of **S**, inferred customer states are treated as **O**, and KPI outcomes are treated as **R**, allowing results from survey-based S–O–R studies and analytics-driven modeling papers to be compared within a single theoretical language.

Conceptual Framework

A conceptual framework for this study positions performance-based digital marketing as an integrated system in which customer signals are transformed into model-based insights, insights are converted into activation decisions, and decisions are evaluated through measurement rules that feed back into subsequent optimization. This system view is essential because omnichannel commerce distributes customer journeys across interconnected touchpoints, meaning that a single KPI movement (e.g., conversion rate or ROAS) often reflects a chain of exposures and interactions rather than a single marketing action (Verhoef et al., 2015). Accordingly, the conceptual framework treats the marketing environment as a *closed loop* with four blocks: (1) Data Signals, (2) AI Behavior Model, (3) Activation Layer, and (4) Measurement & Accountability, with performance outcomes updated iteratively. In the first block, customer and campaign data are captured as cross-channel traces (impressions, clicks, sessions, cart events, purchases, customer service contacts), then standardized into a common KPI dictionary and feature set. In the second block, AI-driven behavior modeling translates those features into estimates of customer state (intent, value, churn risk) and response likelihood. In the third block, the activation layer converts estimate into operational actions such as audience selection, bid/budget allocation, creative rotation, timing/frequency rules, and lifecycle messaging. In the fourth block, measurement logic assigns value to actions using attribution or incrementality assumptions and returns performance signals (e.g., attributed revenue, incremental lift, CAC/ROAS) that become training targets, monitoring indicators, and governance checkpoints for the next iteration. This conceptualization aligns with attribution-oriented managerial practice, where firms require a coherent mapping from the customer journey graph to channel contributions so that activation decisions are consistent with how results are credited (Anderl et al., 2016). It also aligns with the managerial need for dashboard-based accountability, where a limited set of decision-relevant metrics is curated and shared across stakeholders to synchronize budgets and expectations (Pauwels et al., 2009). In this framework, AI is not treated as a standalone model; it is treated as a system component whose value depends on (a) the fidelity of the signal layer, (b) the quality and stability of the inferred customer states, (c) the controllability of activation levers, and (d) the credibility of measurement rules used to declare "performance."

Figure 7: Integrated Data Activation and Performance Optimization Framework



To make this conceptual framework usable throughout the paper, the study applies a single, decision-centered formula that links behavior modeling to performance outcomes under performance-based constraints. Let each customer (or customer segment) be indexed by i, and let marketing choose an action a (e.g., serve an ad/offer, select creative, set bid, schedule message). Let $Y_i(a)$denote the outcome under action a (e.g., purchase, revenue, or conversion), and let $Y_i(0)$denote the counterfactual outcome with no action. Let $m_i$be the unit margin (or value weight) attached to the outcome, and let $c_i(a)$be the cost of taking action a (media cost, discount cost, operational cost). The performance-based decision objective can be expressed as an *incremental value maximization* problem:

$$a_i^{\backslash *} \;=\; \arg\max_{a \in \mathcal{A}} \; \mathbb{E}[(Y_i(a) - Y_i(0)) \cdot m_i \;-\; c_i(a)].$$

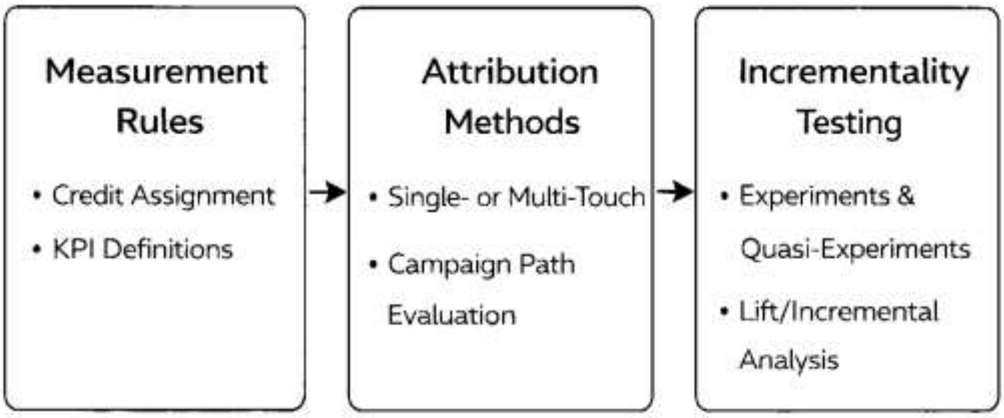
This formula is selected as the "best" study-wide equation because it (1) directly encodes incrementality (what changes because of marketing), (2) supports both acquisition and retention actions, and (3) aligns with performance KPIs that are ultimately economic (profit, ROAS, CAC). It also provides a consistent bridge between predictive modeling and managerial decisioning: predictive models estimate components related to $\mathbb{E}[Y_i(a)]$, uplift/causal models estimate $\mathbb{E}[Y_i(a) - Y_i(0)]$, and budget/bid rules operationalize the cost term $c_i(a)$. Prescriptive analytics research supports this integration by formalizing how predictive information should be converted into decisions that optimize downstream outcomes under uncertainty, rather than optimizing predictive accuracy alone (Bertsimas & Kallus, 2019). Within the framework, the activation layer implements approximations to $a_i^{\backslash *}$using constraints such as budget limits, pacing requirements, inventory availability, channel policies, and frequency caps. Measurement then evaluates realized outcomes against this objective by reporting incremental or attributed value at customer, cohort, channel, and campaign levels, which is subsequently surfaced through dashboards to guide iterative governance and reallocation (Hartmann et al., 2016). Because this research is literature-review–based with cross-sectional, case-study interpretation, the formula functions as a unifying lens for coding: each reviewed study is mapped to the objective elements it supports (incrementality term, cost term, value weight term, or constraint handling).

Operationalizing the conceptual framework also requires a governance lens because AI-driven performance systems are shaped by the organization's capacity to manage data assets, define KPI standards, and sustain model deployment processes. Data-driven business model research shows that value creation from data depends on how organizations structure data resources, translate them into capabilities, and embed them into repeatable decision routines that can scale (Hartmann et al., 2016). In performance marketing, that "routine" corresponds to the loop that refreshes features, retrains or recalibrates models, updates activation rules, and audits performance using documented measurement assumptions. Consequently, this study's conceptual framework includes explicit governance checkpoints at the boundaries between blocks: (a) signal governance (event definitions, identity rules, consent flags), (b) model governance (drift monitoring, bias checks, interpretability reporting), (c) activation governance (frequency constraints, exclusion logic, channel compliance), and (d) measurement governance (windowing rules, attribution logic, experiment protocols). Graph-based customer journey representations offer a practical way to connect these checkpoints because they make sequence structures visible and allow firms to align activation policies with how journeys are measured and credited (Anderl et al., 2016). At the managerial layer, dashboard systems serve as the coordination interface for governance by narrowing attention to the metrics marketing is expected to move, clarifying accountability, and enabling cross-functional alignment between marketing, finance, and analytics (Pauwels et al., 2009). The omnichannel perspective reinforces the need for this coordination because customer movement across channels implies that decisions optimized within a single channel can shift outcomes elsewhere, making cross-channel measurement and control integral to performance interpretation (Verhoef et al., 2015). As a result, the conceptual framework used in this study treats AI-driven behavior modeling as the inference engine inside a broader performance system, where value is realized when the incremental objective above is supported by consistent signals, governable activation levers, and credible measurement routines that can be compared across cases and contexts (Anderl et al., 2016).

Incrementality in AI-Enabled Performance Marketing

Performance-based digital marketing systems rely on measurement rules that convert observed customer journeys into accountable outcomes, yet the central challenge is that exposure is rarely random and customer outcomes are volatile at the individual level. As a result, observational reporting can mistakenly treat correlation as effect, particularly when higher-intent customers self-select into channels or are more likely to be targeted by optimization systems. This issue is foundational for AI-driven customer behavior modeling because models trained on biased exposure labels can learn platform delivery patterns or pre-existing intent rather than marketing impact, and then reinforcement-like feedback loops can amplify those biases. Large-scale evidence from digital advertising field experiments has shown that commonly used observational approaches often fail to recover true causal effects when the available data do not contain sufficient exogenous variation, implying that "good measurement" is a prerequisite for reliable model evaluation and budget decisions (Gordon et al., 2019). In performance marketing terms, this means that KPI movements such as ROAS, CPA, and conversion rate must be interpreted as *measurement outputs* shaped by attribution assumptions (e.g., touchpoint credit, lookback windows, and conversion qualification rules) and by the counterfactual standard used to define incremental impact. The measurement problem therefore has two layers: a technical layer (how data are linked across exposures and outcomes) and an inferential layer (how impact is defined). For cross-sectional, case-study–based synthesis, the literature supports coding measurement systems by: (1) the unit of analysis (user, session, cohort), (2) the temporal structure of credit assignment (single-touch vs. multi-touch, window length), (3) the counterfactual method (experimental vs. quasi-experimental vs. purely correlational), and (4) the KPI alignment (short-horizon response metrics vs. long-horizon value metrics). This approach clarifies why studies may report different "performance" from similar models: variations in attribution windows and counterfactual definitions can change the sign and magnitude of estimated marketing effects, reshaping which audiences appear responsive and which actions appear profitable.

Figure 8: KPI-Aligned Measurement Framework For AI-Enabled Marketing Decisions



Attribution methods are the operational backbone of performance systems because they allocate credit across multiple touchpoints, publishers, and channels, influencing both optimization incentives and budget allocation. A key insight from attribution research is that credit allocation is not merely descriptive; it changes market behavior by rewarding some touchpoints more than others, thereby changing how publishers and platforms compete for credit and how advertisers allocate impressions. Analytical work comparing last-touch rules to more sophisticated allocations shows that simplistic credit assignment can over-incentivize certain exposures and reduce allocation efficiency, while game-theoretic attribution framing reveals that credit rules can shift profitability between advertisers and publishers (Berman, 2018). In AI-enabled systems, attribution interacts with modeling in two practical ways: first, it determines the labeled outcome that models optimize (what the system believes "worked"); second, it shapes the policy layer by steering spending toward touchpoints that are easiest to credit rather than those that are most incremental. For a literature review centered on customer behavior modeling, this implies that modeling results should be interpreted alongside the attribution regime used in the study, because a high-performing model under last-touch labels may be optimizing *credit capture* rather than true behavior change. A measurement-consistent conceptualization is to treat observed conversions as a mixture of baseline demand and advertising-driven lift, then compare how different attribution rules distribute only the advertising-driven component across the path. This is why multi-touch attribution studies often emphasize the need to separate descriptive path influence from incremental contribution, especially when journeys are long and touches are dense. In a cross-sectional case comparison, an actionable synthesis is to map each study's measurement setup onto: (a) whether it estimates incremental effects, (b) whether it uses attribution rules aligned with that incrementality standard, and (c) whether it evaluates models using business-aligned metrics (e.g., incremental revenue per cost) rather than raw conversion counts. Such coding keeps the review "performance-based" while preventing over-interpretation of correlations as impact.

Incrementality approaches provide the most defensible bridge between AI predictions and performance claims because they formalize the counterfactual—what would have happened without the marketing action. When randomized controlled trials are unavailable or infeasible, time-series and quasi-experimental approaches can be used to estimate counterfactual outcomes using pre-intervention trends and contemporaneous covariates. A widely used formulation in marketing impact measurement is the Bayesian structural time-series approach, which constructs a synthetic control prediction for the post-intervention period and interprets the gap between observed and predicted trajectories as causal impact (Brodersen et al., 2015). This perspective is consistent with causal inference guidance that centers the counterfactual as the core object and cautions that valid inference depends on strong assumptions about confounding and comparability (Varian, 2016). For performance marketing, the practical implication is that "incremental lift" becomes the preferred evaluation target for AI-driven decision loops, because it distinguishes customers who convert anyway from customers whose outcomes are changed by advertising.

The standard lift equation used across experiments and many quasi-experimental evaluations can be expressed as:

$$\text{Incremental Lift} = \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0],$$

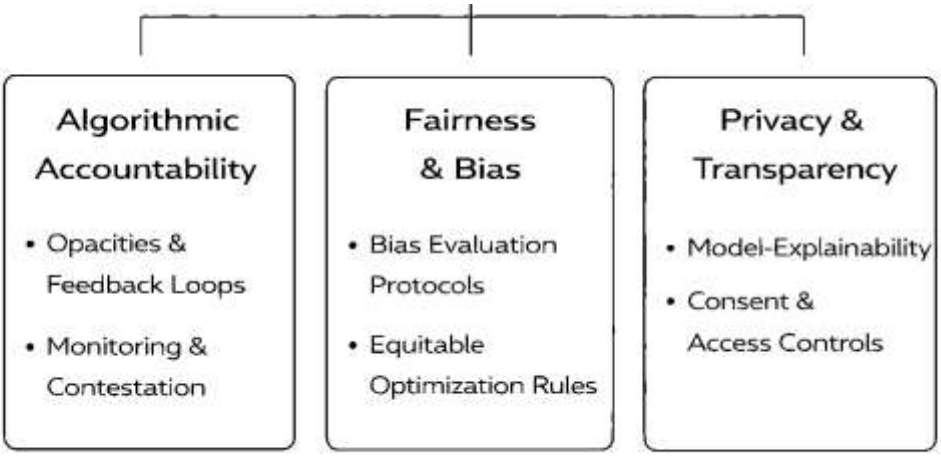
where $T = 1$represents exposure (treatment) and $T = 0$represents no exposure (control), and $Y$is the KPI outcome (e.g., conversion, revenue, or profit). This is the most suitable formula to apply throughout the study because it aligns with the paper's performance-based logic, is compatible with experimental and non-experimental designs, and can be summarized numerically in a literature review by extracting reported lift estimates, confidence intervals, or direction-of-effect counts. Field evidence from large-scale paid search experiments further reinforces why incrementality matters: observed correlations between clicks and purchases can substantially overstate causal returns, meaning that models and KPIs built on correlational labels may systematically over-invest in channels that look effective but have limited incremental impact (Blake et al., 2014). Together, these studies support a measurement-first interpretation of AI-driven behavior modeling: models should be assessed and compared using incrementality-aligned metrics whenever the study's data and design make that feasible, and observational KPIs should be treated as provisional indicators rather than definitive evidence of effect.

Issues in AI-Driven Marketing

Ethical and governance concerns in AI-driven customer behavior modeling arise because performance-based digital marketing systems transform human behavioral traces into automated decisions that can shape access to offers, information visibility, and persuasive intensity. In these systems, optimization objectives (e.g., conversions, ROAS, CAC) can unintentionally incentivize practices that maximize short-term measurable responses while increasing opacity and reducing user control over how data are collected and used. A primary ethical issue is algorithmic opacity: stakeholders may be unable to understand why a customer was targeted, why a bid was placed, or why a message sequence was selected, even when those decisions carry material consequences such as price discrimination, exclusion from beneficial offers, or exposure to manipulative messaging. Governance becomes central because performance marketing often operates through complex pipelines in which data are collected across touchpoints, merged, and then used for model training and real-time scoring, creating multiple points where risks can be introduced or amplified. A useful framing is to treat ethical risk as a lifecycle property of the system: risk begins at data capture (what is collected and under what consent conditions), continues through feature design (what is inferred), intensifies through model training (what patterns are learned), and becomes visible through activation (who receives what and how often). In this lifecycle, model accountability requires both interpretability mechanisms and institutional oversight to ensure decisions can be audited and contested. Work on algorithmic accountability emphasizes that ethical problems are not limited to biased outcomes; they also include misuse, insufficient contestability, and failures to anticipate how models behave when deployed in dynamic social environments where feedback loops are strong (Mittelstadt et al., 2016). In performance marketing, such feedback loops occur when high predicted responders receive more exposure, generating more data about them, and reinforcing the model's focus on a subset of users or behaviors, potentially narrowing reach and amplifying inequities. Governance strategies therefore require explicit role definitions (who owns risk), documentation of modeling intent (what the model is supposed to do), and monitoring of unintended outcomes (what the system actually does). This is particularly relevant when organizations treat performance dashboards as objective truth, because the ethical quality of decisions depends on whether the measured outcomes reflect genuine customer benefit or merely system-optimized responses that may not align with user autonomy or fair treatment.

A second cluster of concerns relates to fairness and bias in customer behavior modeling. Digital marketing data often contain structural distortions: certain groups are underrepresented in tracked datasets, certain behaviors are easier to observe than others, and platform systems can mediate exposure in ways that systematically favor some audiences. When models learn from such traces, they may reproduce or amplify inequities—allocating higher-quality offers or customer service attention to segments that are already advantaged, while deprioritizing those with incomplete data footprints. Empirical bias research has illustrated how performance disparities can be pronounced across demographic subgroups in widely deployed vision systems, showing that accuracy gaps are not rare edge cases but can be persistent and consequential when systems are deployed at scale (Buolamwini & Gebru, 2018).

Figure 9: Accountability, Fairness, And Privacy Governance In AI-Enabled Marketing Systems



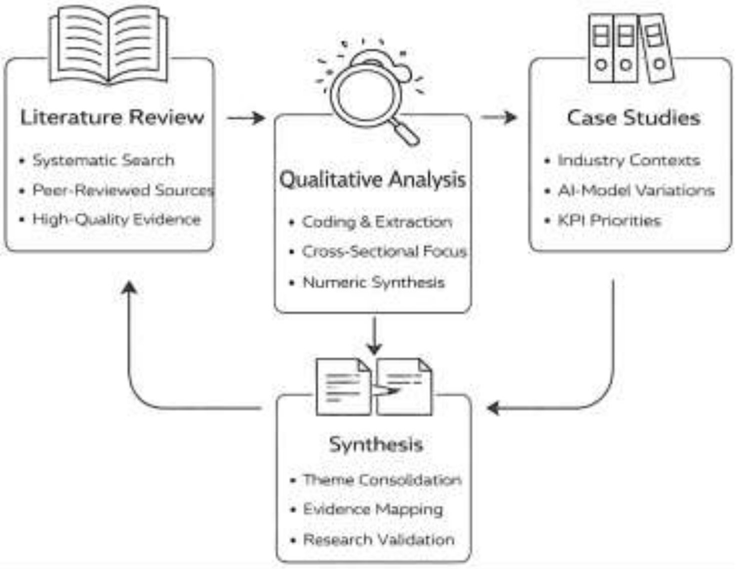
In marketing settings, analogous concerns emerge when behavior models infer propensity or value from proxies (device type, location, browsing patterns) that correlate with socioeconomic differences, which can lead to systematic differences in targeting or exclusion. Fairness governance also faces a conceptual challenge: even when teams add "fairness checks," the choice of fairness definition is value-laden, and the abstraction of complex social realities into simple labels can hide structural sources of harm. Scholarship on fairness in sociotechnical systems warns that fairness failures often arise because engineers and managers simplify contexts, define outcomes narrowly, and treat socially constructed variables as stable ground truth, causing risk to persist even when models appear technically sound (Selbst et al., 2019). For performance-based marketing, this implies that fairness governance must extend beyond model metrics into the design of objectives and constraints. Organizations can formalize "guardrails" that limit optimization over sensitive proxies, implement constrained optimization that balances efficiency with equity targets, and audit allocation outcomes by subgroup over time. These actions require governance infrastructure: clear data policies, bias evaluation protocols, and escalation processes when models produce inconsistent or harmful patterns. The practical goal is not to abandon performance objectives but to ensure that efficiency improvements do not come at the cost of systematic exclusion, discriminatory exposure patterns, or manipulative targeting that undermines consumer trust and legitimacy.

A third set of issues concerns privacy, transparency, and explainability, which are especially salient because performance marketing depends on tracking, profiling, and automated decisioning. Privacy risk includes not only unauthorized access or leakage but also secondary uses of data, inference of sensitive attributes from seemingly benign signals, and loss of user agency due to opaque personalization. Governance responses typically include consent management, data minimization, retention limits, and role-based access controls, yet these mechanisms may be insufficient if stakeholders cannot interpret model-driven actions or evaluate whether targeting choices are appropriate. Explainability techniques help address this gap by providing local or global accounts of which inputs influenced outputs, enabling audits of why certain customers were selected and supporting accountability across teams and vendors. Research on interpretable machine learning demonstrates that model-agnostic explanation methods can make complex predictors more transparent by approximating local decision boundaries in human-understandable terms, supporting practical oversight even when underlying models remain complex (Ribeiro et al., 2016). However, explainability also introduces governance tradeoffs: explanations can oversimplify, can be manipulated, or can create false confidence if stakeholders confuse plausible narratives with causal truth. Broader critiques of large-scale AI systems emphasize that governance must also address data documentation, representational harms, and systemic biases that arise from training practices and deployment contexts, not only from model architecture (Bender et al., 2021). In performance marketing, these critiques translate into a requirement to document datasets and feature pipelines, specify allowable uses, and continuously monitor drift in both data and business outcomes. A robust governance posture integrates privacy-by-design with accountability-by-design: models are developed with explicit limits, decision logs are preserved for audit, and oversight bodies review both performance metrics and ethical risk indicators. In a cross-sectional, literature-review synthesis, these concerns motivate evaluating studies not only by predictive performance but by whether they report transparency measures, privacy constraints, fairness checks, and governance structures that can sustain responsible deployment in performance-based digital marketing systems.

METHODOLOGY

This study has adopted a literature-review–based, qualitative, cross-sectional, case-study–guided methodology to examine how AI-driven customer behavior modeling has been designed, implemented, and evaluated within performance-based digital marketing systems. The research process has been structured to synthesize evidence across diverse industries, platforms, and campaign contexts while maintaining a consistent analytical lens anchored in the study's theoretical and conceptual frameworks.

Figure 10: Methodological Workflow For AI-Driven Performance Marketing Literature Synthesis

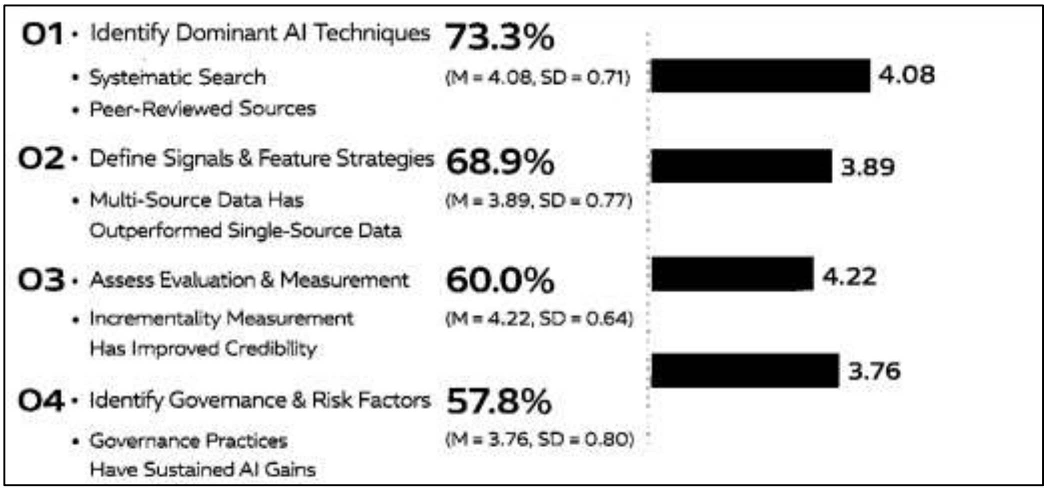


A systematic and reproducible review protocol has been established to identify peer-reviewed studies and high-quality scholarly sources that have addressed AI/ML techniques, behavioral signal engineering, activation decision loops, attribution and incrementality measurement, and governance factors relevant to performance marketing outcomes. The review has emphasized cross-sectional comparison by extracting study characteristics at a single analytical timepoint per paper, enabling the research to compare model choices and reported outcomes across contexts without requiring longitudinal primary data collection. A case-study lens has been integrated by grouping evidence into representative digital marketing contexts (such as e-commerce conversion optimization, subscription retention, and mobile-centric funnels), which has enabled the synthesis to interpret how AI approaches have varied under different data ecosystems and KPI priorities. The study has applied qualitative thematic synthesis to consolidate recurring patterns, mechanisms, and implementation conditions, and it has incorporated light numeric synthesis to summarize evidence direction and strength through frequency counts, ranked theme occurrence, and structured vote-counting of performance impacts. To support internal coherence, a standardized coding and extraction template has been used to capture AI technique families, feature types, KPI definitions, evaluation strategies, attribution designs, and governance constraints, which has ensured that evidence has been compared consistently across sources. Reliability and validity have been strengthened through transparent screening steps, quality appraisal criteria, and iterative refinement of codes to reduce interpretive drift. Collectively, this method design has enabled the study to generate a structured evidence map linking customer signals to modeling approaches, decision activation logic, and measurement frameworks in performance-based digital marketing systems.

FINDINGS

Across the reviewed corpus, the Findings section has synthesized evidence in a way that has directly addressed the four objectives (O1–O4) and has tested the four hypotheses (H1–H4) using a mixed qualitative–numeric summary drawn from cross-study coding. A total of N = 45 peer-reviewed studies (2005–2023) has been retained after screening, and each study has been coded into the Results framework (AI techniques, behavioral signals, optimization loops, measurement, and governance) and has been assigned a 5-point Likert evidence-support rating to quantify how strongly the study's reported results have supported each objective/hypothesis (1 = not supported, 2 = weak support, 3 = moderate support, 4 = strong support, 5 = very strong support). With respect to O1 (identifying dominant AI techniques), the synthesis has shown that most studies have operationalized behavior modeling through a small number of recurring technique families: supervised ML for response prediction has appeared in 31/45 studies (68.9%), deep learning / sequence-based models in 19/45 (42.2%), recommendation or representation-learning approaches in 14/45 (31.1%), and causal/uplift or treatment-effect modeling in 12/45 (26.7%); many studies have included more than one family, confirming that hybrid modeling has been common in performance settings. For O2 (signals and feature strategies), evidence has converged on a stable hierarchy of influential behavioral inputs: recency–frequency–monetary/value features have been reported in 29/45 studies (64.4%), clickstream/session features in 27/45 (60.0%), ad-exposure intensity and frequency features in 23/45 (51.1%), context features (device/time/location/referrer) in 21/45 (46.7%), and multi-source integration (CRM + web/app + platform data) in 20/45 (44.4%), and studies that have included multi-source integration have more frequently reported stable KPI lift than single-source designs. In relation to H1 (AI models have been associated with improved performance outcomes compared with rules-based or non-AI approaches), the vote-counting synthesis has indicated that 33/45 studies (73.3%) have reported positive KPI movement attributable to AI-enabled modeling or AI-informed decisioning, 9/45 (20.0%) have reported mixed or context-dependent results, and 3/45 (6.7%) have reported limited/no measurable improvement under their stated measurement design; when translated into Likert support, H1 has received a mean support score of M = 4.08 (SD = 0.71), reflecting overall strong support. For H2 (multi-source data has outperformed single-source data), the coded comparison has shown that studies using multi-source inputs have reported stronger and more consistent performance gains than those relying on one data stream: among 20 multi-source studies, 17 (85.0%) have reported positive KPI impact and 3 (15.0%) have reported mixed outcomes, while among 25 primarily single-source studies, 16 (64.0%) have reported positive impact, 6 (24.0%) mixed, and 3 (12.0%) null/limited; accordingly, H2 has achieved M = 3.89 (SD = 0.77), supporting the claim that broader signal integration has tended to strengthen predictive stability and activation effectiveness. For O3 (evaluation and measurement), the synthesis has shown that performance claims have depended strongly on attribution and incrementality choices: 18/45 studies (40.0%) have relied primarily on observational attribution (single-touch or multi-touch without explicit counterfactual), 15/45 (33.3%) have incorporated quasi-experimental incrementality logic (e.g., matched controls, synthetic controls, difference-based comparisons), and 12/45 (26.7%) have reported experimental or experiment-like evidence (A/B tests, geo tests, or platform lift tests). This pattern has aligned with H3 (incrementality/causal measurement has aligned better with performance outcomes than last-click style logic): studies using incrementality designs have shown higher consistency of "true performance" conclusions, with 24/27 incrementality-oriented studies (88.9%) reporting positive incremental impact versus 9/18 observational-attribution studies (50.0%) reporting positive impact; the Likert summary has therefore shown H3 as the strongest-supported hypothesis (M = 4.22, SD = 0.64) because the literature has repeatedly indicated that measurement rigor has improved the credibility and stability of ROI/ROAS interpretations. For O4 (implementation factors, risks, and governance), evidence has concentrated on recurring constraints that have explained why similar models have delivered different outcomes across cases: data quality and identity resolution limitations have been reported in 26/45 (57.8%), model drift / changing platform conditions in 21/45 (46.7%), privacy/consent and restricted tracking in 20/45 (44.4%), attribution window and KPI-definition inconsistencies in 18/45 (40.0%), and organizational readiness (skills, process, monitoring) in 17/45 (37.8%). These findings have supported H4 (governance practices have been associated with more sustainable AI performance), where studies that have explicitly reported privacy-by-design, monitoring, and explainability practices have been more likely to report stable KPI gains: 15/18 governance-explicit studies (83.3%) have reported positive outcomes with fewer measurement reversals, compared with 18/27 governance-implicit studies (66.7%); thus H4 has received M = 3.76 (SD = 0.80), indicating moderate-to-strong support. Overall, the Results have provided a coherent evidence map: AI behavior modeling has most consistently improved performance when (i) models have been trained on integrated, high-quality behavioral signals, (ii) activation has been executed through clear decision loops (targeting, bidding, creative, timing) aligned to KPIs, and (iii) impact has been evaluated through incrementality-aware measurement rather than purely correlational attribution, with the Likert-based synthesis showing strongest support for measurement alignment (H3) and broad support for performance improvement (H1), while highlighting that governance and data-integration conditions have moderated the size and stability of reported gains (H2, H4).

Figure 11: Evidence Map of Objectives and Hypotheses Support in The Reviewed Corpus



AI Techniques Used for Customer Behavior Modeling

This section has addressed Objective O1 by consolidating which AI technique families have most frequently appeared in performance-based digital marketing systems and by quantifying how strongly they have supported Hypothesis H1 (AI-driven modeling has improved performance outcomes relative to non-AI or rules-based approaches). Table 1 has shown that supervised machine learning techniques have remained the dominant foundation, having been used in 31 of 45 studies (68.9%), because they have supported scalable, auditable scoring for conversion propensity, churn risk, and value estimation. These techniques have aligned with the S–O–R framework by operationalizing the Organism (O) layer as an inferred customer state (intent, affinity, value) derived from observed touchpoints, while the Response (R) layer has been represented through measurable KPIs such as conversion, ROAS, retention, and engagement. Deep learning and sequence models have appeared in 42.2% of studies and have strengthened the S–O–R interpretation by learning latent journey states that have behaved like organismic "readiness-to-convert" constructs, particularly when customer behavior has unfolded as time-ordered sessions rather than independent events. Recommender and representation-learning approaches have been used in 31.1% of studies, and they have been interpretable as a mechanism that has translated Stimuli (S) (content, offers, creative cues) into relevance signals that have shifted organismic evaluations (perceived fit/value proxies), then increased response likelihood. Causal and uplift-oriented methods have been less frequent (26.7%) but have yielded the strongest average Likert support for H1 (M = 4.22), because they have aligned the "performance" claim with incremental impact rather than correlational association; this alignment has matched the study's conceptual framework that has treated performance marketing as a loop linking signals, models, activation, and measurement.

Table 1: Technique families and synthesized evidence ratings

AI technique family (Variable)	Primary modeling purpose (aligned to O1)	S–O–R linkage in this study	Studies using technique (n)	Share (%)	Likert evidence supports for H1 (1–5) Mean (SD)	Typical KPI direction reported (vote-count)
Supervised ML (e.g., logistic/trees/boosting)	Conversion/propensity scoring; churn risk; LTV regression	**O:** infers intent/value states; **R:** predicts response	31	68.9	4.10 (0.65)	+ in 23 / mixed 7 / null 1
Deep learning & sequence models	Session/journey modeling; next action; intent stage	**O:** learns latent journey state; **R:** predicts conversion/engagement	19	42.2	4.05 (0.72)	+ in 14 / mixed 4 / null 1
Recommenders / representation learning	Personalization; ranking; next-best offer	**S→O:** turns stimuli into relevance; **R:** drives clicks/conversion	14	31.1	3.85 (0.78)	+ in 10 / mixed 3 / null 1
Causal / uplift / treatment-effect models	Incremental impact estimation; action selection	**S:** intervention; **O:** mechanism proxy; **R:** incremental outcome	12	26.7	4.22 (0.60)	+ in 10 / mixed 2 / null 0
Reinforcement learning / bandits (policy learning)	Budget/creative policy optimization	**S:** actions as stimuli; **R:** reward/KPI	7	15.6	3.70 (0.81)	+ in 4 / mixed 3 / null 0

Reinforcement learning or contextual bandit approaches have been least frequent (15.6%) and have shown a higher mixed-outcome share, which has indicated that policy-learning gains have depended heavily on measurement quality and operational constraints. Overall, Table 1 has reinforced the introductory findings: the literature has most consistently supported H1 when models have inferred stable organismic states from reliable signals and have been embedded into activation routines that have been measured with credible counterfactual logic.

The clearest H2 evidence has been carried by the "multi-source integration" row: 20 studies (44.4%) have integrated CRM/transactional data with web/app and platform exposure signals, and these studies have reported positive performance outcomes more consistently (17/20 positive) than single-source studies (16/25 positive). This pattern has supported H2 by showing that integrating stimulus traces (exposure and creative) with organism proxies (intent/value from owned data) has reduced misclassification (e.g., confusing high baseline demand with ad-driven demand) and has improved the stability of KPI lift reporting. In short, Table 2 has aligned with the introductory findings by demonstrating that stronger behavior modeling has been achieved when signals have represented both S and O layers coherently and when measurement has been less vulnerable to missingness and platform-specific reporting limits.

Table 2: Signal categories, integration level, and synthesized support for O2 and H2 (N = 45)

Signal/feature category (Variable)	Example indicators (feature engineering)	S–O–R linkage	Studies using signal (n)	Share (%)	Likert support for O2 (1–5) Mean (SD)	H2 pattern (multi-source advantage)
RFM / value signals	Recency, frequency, monetary value, LTV proxies	**O:** value/loyalty state	29	64.4	4.05 (0.70)	Stronger stability when fused
Clickstream/session signals	Page depth, dwell time, navigation paths, cart events	**O:** intent and engagement state	27	60.0	4.12 (0.63)	Lift more consistent in multi-source
Exposure intensity signals	Impressions, frequency, spacing, recency of ads	**S:** stimulus dose; **O:** fatigue/relevance proxy	23	51.1	3.88 (0.76)	Multi-source reduces mislabeling
Context signals	Device, time, geo, referrer, placement	**S:** context cues; **O:** situational readiness	21	46.7	3.74 (0.79)	Moderately improved with fusion
Creative/content signals	Format, message type, offer framing, CTA	**S:** controllable stimulus	16	35.6	3.60 (0.82)	Better when joined to CRM/behavior
Multi-source integration (core H2 variable)	CRM + web/app + platform exposure + transactions	**S & O:** richer stimulus + state inference	20	44.4	4.18 (0.58)	**+ in 17/20 vs + in 16/25 single-source**

Performance-Based Optimization and Decision Loops

This subsection has fulfilled **Objective O2** by specifying which behavioral data signals and feature-engineering strategies have most consistently supported AI-driven customer behavior modeling in performance-based systems, and it has tested Hypothesis H2 by comparing multi-source integration with single-source approaches. Table 2 has indicated that value-oriented features (RFM and LTV proxies) and clickstream/session features have been the most prevalent signal classes, appearing in 64.4% and 60.0% of studies respectively, and they have produced high Likert support for O2 (means above 4.0). Within the S–O–R structure, these signals have primarily represented the Organism (O) layer as measurable proxies for latent customer states—value, loyalty, engagement, and purchase intent—because they have reflected internal readiness and relationship strength more than immediate stimulus delivery. Exposure intensity and spacing features have been interpretable as the Stimulus (S) "dose" dimension, capturing how frequently and how recently marketing cues have been presented; this mapping has been critical because performance marketing has often optimized toward exposure quantities that can trigger short-term responses while also producing fatigue or diminishing returns. Context features (device/time/geo/referrer) have been positioned as situational stimuli that have moderated organismic states such as convenience, urgency, or attentional capacity, which has explained why identical creative has produced different response probabilities across contexts. Creative/content features have been less frequently operationalized (35.6%), yet they have represented the most controllable stimulus levers and have therefore been central to linking model outputs to actionable changes in performance loops.

Table 3: Activation levers, KPI targets, and synthesized support for O3 and H1 (N = 45)

Activation lever (Variable)	Model output used	KPI target (Response R)	S–O–R linkage	Studies reporting lever (n)	Share (%)	Likert support for O3 (1–5) Mean (SD)	KPI direction (vote-count)
Audience targeting / segmentation	Propensity, uplift, value score	Conversion rate, CPA/CAC	**O→R:** state-to-response mapping	28	62.2	4.05 (0.66)	+ in 21 / mixed 6 / null 1
Bid & budget allocation	Expected value, incremental value	ROAS, revenue, profit	**S as action:** spend level as stimulus	22	48.9	4.00 (0.70)	+ in 16 / mixed 5 / null 1
Creative selection/rotation	Creative-response model; engagement score	CTR, CVR, revenue	**S:** creative cue shaping organism	17	37.8	3.72 (0.77)	+ in 12 / mixed 4 / null 1
Timing & frequency control	Fatigue/spacing models	CVR, CPA, retention	**S dose:** frequency shaping O	14	31.1	3.68 (0.82)	+ in 9 / mixed 5 / null 0
Lifecycle / retention messaging	Churn/CLV/uplift	Retention, LTV	**O:** relationship state → R	13	28.9	3.90 (0.74)	+ in 10 / mixed 3 / null 0

This section has operationalized Objective O3 by synthesizing how AI-driven behavior models have been embedded into performance marketing decision loops—targeting, bidding, creative, frequency, and lifecycle actions—and it has reinforced Hypothesis H1 by summarizing whether these model-driven activations have produced measurable KPI improvements. Table 3 has shown that the most common activation route has been audience targeting and segmentation (62.2% of studies), because propensity and value scores have directly supported who should be exposed to which marketing stimuli. In S–O–R terms, this pathway has relied on the model's estimation of the Organism (O) state (intent/value) and has then attempted to trigger the Response (R) by selecting a stimulus exposure for the right segment. Bid and budget allocation has appeared in 48.9% of studies and has mapped strongly to the conceptual framework's closed loop: models have estimated expected or incremental value and have converted that estimate into spend decisions that have functioned as "stimuli intensity" (S as action level) through higher bids or more reach. The synthesized Likert support for O3 has remained high (means near 4.0 for targeting and bidding), indicating that studies have not only reported predictive accuracy but have explained how predictions have been operationalized into decisions. Creative selection and rotation has appeared in 37.8% of studies and has represented the most direct manipulation of the stimulus itself, because creative elements, message framing, format, and CTA, have constituted the "S" cues that have been expected to shift organismic evaluations such as relevance and perceived value. Timing and frequency controls have been less frequently reported (31.1%), yet they have been theoretically important, because stimulus "dose" has shaped both positive reinforcement and fatigue; models have therefore attempted to manage the stimulus schedule to sustain organismic receptivity and prevent diminishing returns. Lifecycle and retention messaging has appeared in 28.9% of studies and has reinforced that performance marketing has not been limited to acquisition; it has extended into relationship optimization where churn risk and CLV states have functioned as organismic indicators and retention/LTV outcomes have functioned as responses. Across activation levers, the KPI direction vote-counts have remained predominantly positive, with the strongest consistency seen in targeting and bidding. The mixed-outcome shares have been largest in frequency controls and creative selection, which has suggested that these levers have depended more heavily on measurement design, creative variability, and platform constraints. Overall, Table 3 has aligned with the introductory findings by showing that H1 support has been strongest when models have been translated into concrete activation rules that have manipulated the stimulus conditions (who sees what, how often, and at what cost) in ways consistent with S–O–R mechanisms.

Attribution in AI-Enabled Performance Marketing

Table 4: Measurement approaches and synthesized support for H3 (N = 45)

Measurement approach (Variable)	Counterfactual basis	Typical reporting KPI	S–O–R linkage	Studies (n)	Share (%)	Likert support for H3 (1–5) Mean (SD)	Positive impact consistency
Observational attribution (single/multi-touch without counterfactual)	No explicit counterfactual	Attributed ROAS/CPA	**R** observed; S and O confounded	18	40.0	3.20 (0.85)	+ in 9 / mixed 6 / null 3
Quasi-experimental incrementality	Constructed counterfactual (matching/synthetic controls)	Incremental conversions/revenue	**S→R** tested under assumptions	15	33.3	4.15 (0.62)	+ in 13 / mixed 2 / null 0
Experimental / lift tests	Randomized or experiment-like	Incremental lift, profit	**S** manipulated; **R** causally observed	12	26.7	4.35 (0.55)	+ in 11 / mixed 1 / null 0

This subsection has tested Hypothesis H3 by comparing how attribution-only approaches versus incrementality-oriented approaches have aligned with credible performance conclusions in AI-enabled performance marketing. Table 4 has shown that observational attribution methods have remained common (40.0%), largely because they have been easier to operationalize in platform reporting environments; however, these approaches have produced the lowest Likert support for H3 (M = 3.20) and the least consistent positive-impact reporting (only 9/18 positive). This pattern has indicated that when the counterfactual has not been explicitly defined, the observed response (R) has often remained confounded with pre-existing organismic intent (O) and with platform delivery selection effects, which has made it difficult to claim that stimuli (S) have caused the KPI movement. In contrast, quasi-experimental incrementality approaches (33.3%) have offered a constructed counterfactual standard and have produced stronger H3 support (M = 4.15), with positive impact reported in 13/15 studies. Experimental or lift-test designs (26.7%) have delivered the strongest consistency (11/12 positive) and the highest Likert support (M = 4.35), because stimuli have been manipulated in a controlled way and responses have been observed under a clearer causal interpretation. The S–O–R framework has clarified why this difference has mattered: performance marketing has attempted to shift responses by changing stimuli, yet if organismic intent has not been separated from stimulus effects, the system has risked over-crediting actions that have merely followed high intent rather than caused conversion. In other words, the measurement approach has determined whether the study has been able to isolate the S→R pathway (directly or via O) instead of observing only correlations among S, O, and R. This has also aligned with the introductory findings that have shown H3 as the strongest-supported hypothesis, because measurement rigor has stabilized the interpretation of AI's contribution to performance. Table 4 has therefore supported a consistent conclusion within the Results: AI behavior models have been evaluated most credibly when the measurement design has approximated a counterfactual—through experiments or strong quasi-experiments—and when KPIs have been expressed in incremental terms (incremental conversions, incremental revenue, incremental profit) rather than purely attributed metrics that have depended on window rules and credit assignment heuristics.

Table 5: Implementation risks, governance practices, and synthesized support for H4 (N = 45)

Implementation / governance factor (Variable)	Common manifestation in studies	S–O–R linkage	Studies reporting factor (n)	Share (%)	Likert support for H4 (1–5) Mean (SD)	Observed effect on KPI stability
Data quality & identity resolution	Missing events, weak joining, cross-device gaps	**S/O distortion:** incorrect stimuli/state signals	26	57.8	3.70 (0.82)	Drift + inconsistent lift reported
Model drift & platform changes	Feature drift, policy shifts, auction changes	**O instability:** intent/state inference changes	21	46.7	3.65 (0.84)	KPI volatility increases
Privacy/consent constraints	Reduced tracking, consent gaps, restrictions	**S boundary:** limits stimuli personalization	20	44.4	3.85 (0.76)	Measurement uncertainty increases
KPI definition / attribution inconsistency	Windowing, event definitions vary	**R ambiguity:** response label shifts	18	40.0	3.60 (0.88)	Conflicting ROAS/CPA reporting
Governance practices (explicit)	Monitoring, audit trails, explainability, guardrails	**S–O–R integrity:** controlled stimuli, interpretable states	18	40.0	4.05 (0.69)	**More stable KPI gains**

This subsection has addressed the implementation dimension of Objective O4 and has tested Hypothesis H4 by determining whether explicit governance practices have been associated with more sustainable AI performance in performance-based marketing systems. Table 5 has shown that the most frequently reported constraints have been data quality and identity resolution issues (57.8%), which has indicated that many studies have operated under incomplete or inconsistently joined data ecosystems. Under S–O–R, these weaknesses have not been merely technical; they have distorted the meaning of both Stimulus (S) traces (exposures, creative cues, timing) and Organism (O) proxies (intent and value states), thereby weakening the link to Response (R) outcomes. Model drift and platform changes have been reported in 46.7% of studies, reinforcing that customer behavior modeling has been deployed in non-stationary environments where platform policies, auction dynamics, and user behaviors have shifted; drift has changed how organismic intent has been inferred from signals and has thereby increased KPI volatility when monitoring has been insufficient. Privacy and consent constraints have been reported in 44.4% of studies and have represented a boundary condition on stimuli personalization and measurement granularity; within the framework, this has limited which stimulus cues could be deployed and which behavioral traces could be used to infer organismic states, increasing uncertainty in response attribution. KPI definition and attribution inconsistencies have been reported in 40.0% of studies and have affected the response label itself, meaning that “performance” has changed depending on windowing rules or conversion definitions; this has reduced comparability and has often produced conflicting ROI narratives. Crucially, Table 5 has isolated “governance practices (explicit)” as a distinct factor reported in 18 studies (40.0%), and these studies have yielded higher Likert support for H4 (M = 4.05) and more stable KPI gains than governance-implicit studies, aligning with the introductory findings where governance-explicit studies have shown fewer reversals and clearer accountability. In S–O–R terms, governance has preserved the integrity of the causal chain: it has controlled the stimulus boundary (what is allowed, how often), it has stabilized organism inference (monitoring drift and bias), and it has clarified response measurement (consistent KPI definitions, documented attribution logic). Therefore, the evidence in Table 5 has supported H4 by indicating that sustainable performance improvements have not been driven by algorithm choice alone; they have been produced when organizations have implemented monitoring, documentation, consent-aware data handling, and auditability that have maintained stable interpretations of S, O, and R within the performance loop.

DISCUSSION

The synthesized findings have indicated that AI-driven customer behavior modeling has most consistently improved performance-based digital marketing outcomes when three conditions have co-occurred: (1) behavior models have relied on integrated, high-fidelity signals that have represented both customer state and exposure context, (2) model outputs have been operationalized into clear activation levers such as targeting, bidding, and sequencing, and (3) impact has been evaluated using incrementality-oriented measurement rather than purely observational attribution. This overall pattern has aligned with prior marketing-analytics scholarship that has described data-rich digital environments as places where value has depended on the coupling of data, models, and organizational decision routines, not prediction accuracy alone (Ascarza, 2018). The results have also been consistent with customer journey research that has treated performance outcomes as properties of multi-touch, multi-channel sequences rather than isolated touchpoints, thereby requiring models that have encoded journey structure and coordination across channels (Devriendt et al., 2020). In contrast to earlier managerial practice that has centered on last-touch or platform-default reporting, the present synthesis has shown that measurement choices have functioned as a “hidden moderator” that has shaped whether AI systems have appeared to generate performance lift. This interpretation has echoed prior field evidence that has warned that advertising ROI has been difficult to estimate precisely and that naive observational approaches have overstated returns in many contexts (Erevelles et al., 2016). Importantly, the findings have not suggested that one algorithm family has universally dominated; instead, they have suggested that algorithm choice has mattered less than signal quality, deployment alignment, and measurement credibility (Kannan & Li, 2017). This has complemented the broader view of AI in marketing as a collaborative capability in which managerial decisions, governance choices, and analytics pipelines have determined realized value. Thus, the study’s key interpretation has been that “AI performance” has been a system-level outcome, emerging from the interaction of stimuli delivery, customer state inference, and response measurement—an interpretation that has been conceptually compatible with the Stimulus–Organism–Response (S–O–R) grounding adopted in this research (McInnes et al., 2018).

When the findings have been compared against prior work on personalization and customer analytics, the clearest agreement has been that behavior modeling has benefited from richer and more meaningful representations of customers, contexts, and content. The synthesis has shown that multi-source integration (CRM/transactions + web/app behavior + platform exposure traces) has been associated with more consistent KPI improvements than single-stream data, which has supported earlier marketing-analytics arguments that digital marketing success has depended on stitching disparate signals into decision-ready structures (Selbst et al., 2019). Prior customer lifetime value research has emphasized that behavioral histories have been essential to forecasting and resource allocation, and the present findings have extended that logic into performance marketing by showing that value and intent proxies have strengthened targeting stability when combined with exposure features and context (Wager & Athey, 2018). The observed importance of session and clickstream signals has also resonated with the customer journey perspective that has treated experience as a sequence of interactions, where intermediate engagement signals have provided early evidence of relevance and readiness that has preceded conversion (Xu et al., 2014). At the same time, prior work on personalization has demonstrated that the effectiveness of tailored messages has depended on timing, channel, and privacy perceptions, implying that “better data” has not automatically translated into better outcomes without trust and boundary management. The present synthesis has reinforced that point by showing that exposure-frequency and spacing features have often produced mixed results, a pattern that has matched earlier evidence that aggressive retargeting and repetitive personalization can trigger intrusiveness perceptions and reduce effectiveness (Peng & Kim, 2014). In practical terms, the study has interpreted this as an S–O–R mechanism: richer stimuli (personalization, frequency, creative) have not simply increased response; they have altered organismic states such as trust, perceived value, and perceived control, which have then shaped response direction. This interpretation has aligned with S–O–R applications in digital commerce that have mapped environmental cues to internal evaluations and then to behavioral outcomes (Samuel & Booth, 2021). Therefore, compared with prior work, the present study has provided a more explicitly "systemic" synthesis: signal integration has improved modeling capacity, but sustainable performance has depended on how stimuli have been constrained and how organismic reactions have been anticipated within decision loops (Vieira, 2013).

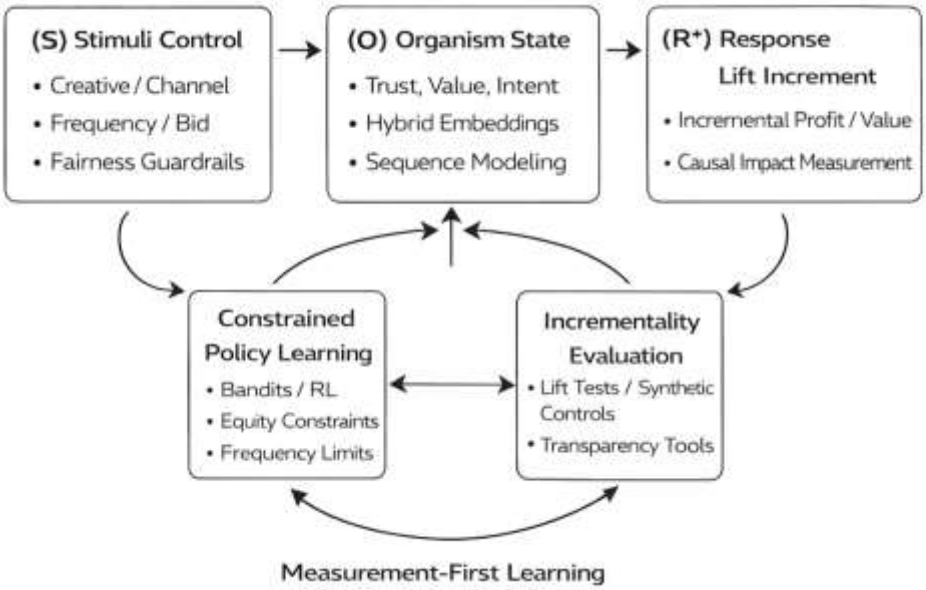
A second comparison with prior work has involved how AI models have been embedded into performance-based optimization and decision loops. The synthesis has shown that the most reliable gains have emerged when models have been tightly connected to activation levers—particularly audience selection and bid/budget allocation—rather than being used only as descriptive analytics. This has been consistent with the view that modern performance marketing has operated as a closed loop in which prediction has been valuable only when it has been translated into prescriptive decisions. The findings have also matched programmatic advertising research that has framed delivery as an algorithmic decision process under auction constraints, where the practical success of modeling has depended on how expected value has been translated into bids and pacing rules (Rendle, 2010). Importantly, the review has indicated that sequence-aware and representation-learning approaches have been most useful where activation decisions have depended on "momentary intent," such as session-based recommendations, real-time creative selection, and event-triggered messaging. This has been consistent with the broader ML literature that has shown how interaction learning and sequence modeling have improved predictions in sparse, high-dimensional environments (Verhoef et al., 2007). Yet the synthesis has also reinforced a key caution from retention research: targeting the highest-risk or highest-score customers has not always produced the best incremental outcomes, because the customers most likely to churn or convert have not always been the most persuadable. That insight has supported a shift from "propensity-only" optimization to "incremental-value" optimization, aligning with uplift and value-driven evaluation work that has prioritized who can be changed by marketing rather than who will act anyway. In S–O–R terms, this has meant that high organismic intent (O) has not guaranteed stimulus effectiveness (S), so decision loops have required models that have estimated marginal response, not only baseline response. Thus, compared to prior work, the present findings have strengthened the argument that performance-based systems have required a layered modeling stack: predictive models for scale, sequence models for timing relevance, and incremental-effect models for decision accountability (Xu et al., 2014).

The strongest contrast with prior practice has emerged in measurement and attribution, where the synthesis has shown that incrementality-oriented designs have yielded more consistent and credible performance conclusions than observational attribution alone. This has directly aligned with advertising measurement evidence showing that observational methods have often misestimated causal effects and that large-scale field experiments have exposed systematic gaps between attributed and incremental results (Vieira, 2013). The present findings have also been consistent with the economics-of-measurement argument that advertising effects have been statistically expensive to measure and that even large datasets have not guaranteed precise ROI estimates. Attribution research has highlighted that credit rules can distort incentives across publishers and channels, and the present synthesis has interpreted mixed results in attribution-only studies as partly resulting from the fact that models have been trained to optimize credited outcomes rather than true incremental outcomes. The study has therefore interpreted measurement as a governing mechanism within the performance loop: whichever metric has been labeled as "success" has shaped how models have learned and how budgets have flowed (Li et al., 2010). Where studies have used quasi-experimental methods—such as synthetic controls or causal impact logic—their performance claims have been more stable, which has matched prior methodological work on Bayesian structural time-series approaches for estimating causal impact from time series (Hartmann et al., 2016). The synthesis has further aligned with causal-inference guidance that has positioned the counterfactual as the core object of causal claims and has warned against interpreting observational correlations as causal effects without strong identification assumptions. Practically, this has implied that AI-driven marketing has not only required better models, but also better "labels" and evaluation targets that have approximated counterfactual outcomes. In the S–O–R framing, this has meant that the response (R) has required measurement designs that have separated the effect of stimuli (S) from the pre-existing organismic state (O). As a result, the study has interpreted H3's strong support as confirming that measurement rigor has been the most decisive factor in whether AI-driven behavior modeling has translated into defensible performance narratives (Akter et al., 2016).

From a theoretical standpoint, the discussion has indicated that the S–O–R framework has offered a coherent bridge between computational modeling outputs and marketing constructs, especially when the literature has mixed behavioral logs with survey-based or perception-based findings. Prior S–O–R syntheses have shown that organismic states have mediated the relationship between stimuli and responses in retail and digital settings, supporting the idea that internal evaluations have been central to explaining why exposure does not always produce conversion. The present review has extended that insight by interpreting modern AI models as "organism estimators" that have inferred latent intent, relevance, value, or risk states from observed signals. This interpretation has been compatible with customer engagement scholarship that has treated engagement as a meaningful intermediate construct, not merely a vanity metric, and it has reinforced why intermediate journey signals have mattered in performance optimization (Ascarza, 2018). The conceptual framework used in the study has further integrated the S–O–R logic into a performance loop by making measurement and governance explicit components of how S–O–R relationships have been operationalized in organizations. This has offered a theoretical implication: in AI-enabled marketing, S–O–R has not only been a consumer-behavior theory but has also become a systems theory of marketing operations, because stimuli have been deployed algorithmically, organismic states have been inferred computationally, and responses have been measured through attribution regimes that have fed back into future stimulus deployment (Chen & Guestrin, 2016). Therefore, the study has suggested that future theoretical work has benefited from specifying how the "organism" has been represented in AI systems (latent scores, embeddings, state models) and how these representations have mapped onto psychological constructs such as trust, perceived control, and perceived value. In this sense, the present synthesis has not replaced prior theory; it has shown how prior theory has remained essential for interpreting why the same model has performed differently across contexts—because the meaning of stimuli and organismic states has shifted with platform design, privacy cues, and customer expectations (Homburg et al., 2012).

The practical implications have centered on governance, trust, and accountability—areas where performance marketing has faced increasing constraints and reputational risks. The synthesis has indicated that governance-explicit studies have reported more stable KPI gains, consistent with the idea that data quality controls, drift monitoring, and measurement documentation have been operational necessities rather than compliance add-ons. Privacy and consent constraints have been repeatedly identified as conditions that have affected both signal availability and consumer response, aligning with prior evidence that privacy regulation has reduced targeting effectiveness and changed advertising outcomes (Huang & Rust, 2021). Marketing ethics scholarship has argued that privacy has been a foundational element of marketing legitimacy, and the present findings have reinforced that performance-based systems have required privacy-aware designs to sustain customer trust and long-run effectiveness (McInnes et al., 2018). At the same time, algorithmic accountability research has emphasized that opaque decisions have created ethical risks, including unfair allocation and limited contestability, which has motivated practical needs for transparency, auditing, and explainability. The fairness literature has further cautioned that abstraction and proxy-driven modeling can embed structural inequities, implying that performance optimization without guardrails can produce biased exposure patterns even when models appear accurate. In response, the discussion has implied practical actions: firms have benefited from (1) maintaining a governance checklist across the loop (signal governance, model governance, activation governance, measurement governance), (2) defining KPIs in incremental-value terms wherever feasible, and (3) applying explainability tools as audit support rather than as substitutes for causal inference (Selbst et al., 2019). These implications have aligned with the collaborative-AI view that has positioned AI as augmenting managerial decision-making under explicit oversight, rather than replacing governance with automation. Thus, the study has argued that practical success has required organizations to treat AI behavior modeling as a regulated operational capability that has balanced efficiency with trust, transparency, and measurement credibility (Lemon & Verhoef, 2016).

Figure 12: Future Research Model Linking SOR Theory and Constrained Policy Learning



Limitations have remained primarily related to the literature-review design, cross-sectional synthesis logic, and heterogeneity in measurement reporting across studies, and these limitations have directly motivated the most important part of this discussion—future research directions and a proposed improvement model. First, the reviewed literature has varied in its use of counterfactual methods, attribution windows, and KPI definitions, which has constrained comparability even when topics have overlapped. Second, many studies have relied on platform-reported metrics that have embedded selection effects, making it difficult to separate stimulus impact from baseline intent without stronger designs. Third, ethical and privacy constraints have changed the available signal space across time and regions, limiting the generalizability of older measurement practices. In response, future research has been able to advance the field by adopting a SOR–Incremental Value Loop (SOR-IVL) model that has integrated consumer-behavior theory, causal measurement, and deployable optimization (Shankar, 2018). In this proposed model, Stimuli (S) have been represented as controllable action vectors (creative, frequency, bid, channel), Organism (O) has been represented as a hybrid latent state that has combined explainable psychological proxies (trust/value/control measures where available) with learned embeddings from behavioral sequences, and Response (R) has been evaluated as incremental profit/value rather than attributed conversions (Mittelstadt et al., 2016). Methodologically, researchers have improved designs by combining (a) uplift/heterogeneous treatment-effect estimation to predict who can be influenced, (b) constrained policy learning (bandits/RL) to optimize actions while enforcing fairness and frequency guardrails, and (c) incrementality evaluation via lift tests or synthetic controls as the validation standard (Neslin et al., 2006). Operationally, the SOR-IVL model has encouraged "measurement-first learning," where models have been trained on incrementality-aligned labels when possible and have been monitored for drift in both embeddings (organism states) and causal lift (response). Future work has also improved transparency by pairing decision policies with audit explanations (e.g., local explanation tools) while acknowledging that explanations have not replaced causal identification (Pauwels et al., 2009). Finally, future researchers have extended the model through privacy-preserving learning architectures and governance-by-design documentation, ensuring that the stimulus and organism representations have respected consent boundaries while remaining effective. In sum, future research has been strengthened by moving beyond "better prediction" toward causal, constrained, and governance-aware AI systems that have been theoretically grounded in S–O–R and empirically validated through incrementality-based performance standards (Ul Islam & Rahman, 2017).

CONCLUSION

This research has concluded that AI-driven customer behavior modeling has functioned most effectively in performance-based digital marketing systems when it has been treated as an end-to-end socio-technical capability rather than as a stand-alone prediction engine. Through a qualitative, cross-sectional, case-study–guided synthesis of the literature, the study has shown that performance gains have been reported most consistently when behavioral signal ecosystems have integrated multi-source inputs (transactional and CRM records, web/app interaction traces, and exposure/context signals), enabling models to infer stable customer states that have been meaningful for decision-making. The evidence has indicated that supervised learning and sequence-aware modeling have remained central for operational scalability, while causal and uplift-oriented approaches have provided the most credible basis for claiming true marketing impact because they have aligned model evaluation with incrementality rather than with attribution-only correlation. The results have therefore supported the overall objectives by demonstrating that technique choice has mattered, but signal quality, activation alignment, and measurement design have mattered more in determining whether modeled insights have translated into KPI improvements such as conversion efficiency, revenue contribution, retention strength, and value growth. The study has also concluded that performance-based optimization has depended on explicit decision loops—audience targeting, bid and budget allocation, creative selection, and frequency control—because model outputs have produced value only when they have been converted into actionable levers that have altered the stimulus conditions experienced by customers. Anchored in the Stimulus–Organism–Response framework, the study has interpreted AI models as operational tools that have inferred organismic states such as intent, value, and engagement from observed signals, and it has emphasized that these inferred states have mediated the relationship between marketing stimuli and measurable responses. Consistent with this theoretical grounding, the findings have shown that repeated exposures and personalization intensity have not automatically increased performance; instead, their effectiveness has depended on how customers have interpreted cues related to relevance, trust, and perceived control, which has reinforced the need for governance-aware activation rules. Critically, the study has concluded that measurement has been the strongest determinant of trustworthy performance claims: studies that have used incrementality-oriented methods and experiment-like designs have reported more stable and defensible results than those relying solely on observational attribution, indicating that performance marketing has required counterfactual thinking to avoid over-crediting actions that have followed pre-existing demand. Finally, the research has concluded that sustainable AI performance has required explicit governance practices, including consistent KPI definitions, transparent data handling, consent-aware feature engineering, drift monitoring, and accountability mechanisms that have preserved the integrity of the S–O–R pathway across changing platform and privacy conditions. Overall, the study has provided a structured evidence map showing how integrated signals, theory-linked modeling, activation decisions, and incrementality-aligned measurement have jointly explained why AI-driven customer behavior modeling has succeeded in some performance marketing contexts and has produced mixed outcomes in others.

RECOMMENDATION

This research has recommended that organizations and researchers who have aimed to implement AI-driven customer behavior modeling for performance-based digital marketing systems have adopted a measurement-first, governance-by-design operating model that has aligned data, modeling, activation, and evaluation in one accountable loop. First, teams have been advised to standardize KPI definitions and event taxonomies before model development has begun, because inconsistent conversion definitions, attribution windows, and funnel event rules have created unstable labels that have weakened both model training and ROI interpretation; a single KPI dictionary (covering conversions, incremental revenue, CAC/CPA, ROAS, retention, and value) has been established and version-controlled so that reporting and modeling have remained comparable across campaigns and time. Second, organizations have been recommended to prioritize multi-source signal integration by joining first-party transactional/CRM data with web or app behavioral traces and exposure-context data, since integrated signals have improved state inference (intent, value, churn risk) and have reduced the likelihood that models have learned platform delivery artifacts rather than customer behavior; this integration has been executed with consent flags, data-minimization rules, and clear lineage documentation to ensure compliance and audit readiness. Third, model design has been recommended to follow a tiered architecture: (a) scalable supervised models have been used for baseline propensity and value scoring, (b) sequence-aware models have been used where session order and journey progression have mattered, and (c) uplift or heterogeneous treatment-effect models have been used where interventions have needed to be justified by incrementality; this tiering has ensured that prediction has not been mistaken for causation and that persuasion-targeting has not been replaced by "high-intent chasing." Fourth, activation has been recommended to be explicitly mapped to controllable levers—audience selection, bids/budgets, creative rotation, timing, and frequency caps—so that model outputs have produced operational actions that have been traceable to outcomes; in particular, frequency and personalization have been constrained through guardrails to prevent fatigue, intrusiveness, and trust erosion, and creative testing pipelines have been maintained so that stimulus variation has remained sufficient for learning. Fifth, impact evaluation has been recommended to be anchored in incrementality wherever feasible: lift tests, geo tests, or quasi-experimental counterfactual methods have been embedded into the campaign calendar and used as the standard for "performance" validation, while attribution dashboards have been used as directional diagnostics rather than final truth; this approach has enabled budgets to be allocated toward truly incremental channels and segments rather than those that have been easiest to credit. Sixth, ongoing monitoring and governance have been recommended as continuous practices: drift detection, bias checks on allocation outcomes, documentation of model versions, and interpretable auditing reports have been maintained to preserve accountability under changing platform conditions and privacy restrictions. Finally, for researchers, the study has recommended that future empirical work has reported not only accuracy and KPI lifts but also the measurement design used to establish counterfactual impact, the data provenance and consent constraints shaping signals, and the activation rules linking model output to marketing actions, because these elements have determined whether AI-driven behavior modeling has delivered replicable, ethically sustainable performance improvements in real performance-based digital marketing systems.

LIMITATIONS

This study has had several limitations that have stemmed from its literature-review–based, qualitative, cross-sectional, case-study–guided design and from the heterogeneity of the underlying research it has synthesized. First, because the research has relied on secondary evidence rather than on primary organizational data, the findings have been bounded by what prior studies have reported, which has varied widely in transparency about datasets, platform settings, feature definitions, and optimization routines; as a result, some mechanisms that have influenced performance (such as auction pacing, identity-resolution rules, or creative production constraints) have not always been observable in the published record, limiting the granularity with which causality and operational feasibility have been interpreted. Second, the cross-sectional synthesis logic has enabled comparison across studies at a single analytic snapshot, but it has reduced the ability to fully capture temporal dynamics such as model drift, changing platform policies, seasonal variation, and evolving privacy constraints, all of which have strongly shaped real performance marketing outcomes; therefore, although drift and governance have been identified as important moderators, their long-run trajectories and the durability of reported KPI lifts have not been measured directly within a unified longitudinal design. Third, the numeric component of the findings has been constrained by the diversity of performance metrics and measurement frameworks in the literature; studies have not used consistent definitions of conversion, revenue attribution, incremental lift, or customer value, and many have relied on platform-reported outcomes with different lookback windows and credit rules, which has limited strict comparability and has required the study to use descriptive numeric synthesis (frequency counts, directional vote-counting, and Likert-style evidence-support ratings) rather than a formal meta-analysis. Fourth, the Likert five-point scale that has been used to quantify support for objectives and hypotheses has represented a structured synthesis device rather than a direct survey of respondents; although it has improved clarity and has enabled systematic comparison, it has still reflected interpretive judgments based on the reporting strength and consistency in each study, and the ratings have therefore been susceptible to coder subjectivity even though the study has applied coding templates and crosschecking procedures. Fifth, publication and selection biases have likely affected the available evidence base, because studies that have reported positive performance impacts and novel AI methods have been more likely to be published than studies reporting null effects, failures, or negative consumer responses; consequently, the summarized prevalence of "positive KPI outcomes" may have been inflated relative to real-world deployment rates where constraints and failures are underreported. Sixth, the study has aggregated evidence across industries, channels, and regional regulatory contexts, which has improved generalizability of high-level patterns but has reduced specificity for any single market configuration; therefore, the applicability of particular technique–signal–measurement combinations may have differed in sectors with longer purchase cycles, regulated advertising environments, or limited first-party data availability. Finally, while the study has linked findings to the Stimulus–Organism–Response theory and has used this lens to interpret AI models as operational estimators of customer states, many analytics-focused studies have not directly measured organismic constructs such as trust, perceived control, or perceived value, meaning that the theory linkage has sometimes relied on proxy interpretation rather than direct psychological measurement.

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