Publisher

Vandana Publications
www.vandanapublications.com

International Journal of Engineering and Management Research

2026 Volume 16 Number 4 August

E-ISSN:2250-0758
P-ISSN:2394-6962

Research Article

Customer Lifetime Value

Modelling Customer Lifetime Value under Endogenous Marketing Interventions: A Structural Bayesian Approach

Ghanvat S[1], Joshi S[2], Shintre A[3*]

DOI:10.31033/IJEMR/16.4.2026.1938

[1] Sudipkumar Ghanvat, Sr. Director & Head - Data & AI, VRIO Digital Dallas, United States of America.

[2] Shreya Joshi, Sr. Data Analyst, American Airlines, Texas, United States of America.

[3*] Aditi Shintre, Research Engineer, Neowesolutize Technology Pvt. Ltd., Pune, Maharashtra, India.

Customer lifetime value (CLV) is the present value of future profits from customer relationships and serves as a fundamental metric for resource allocation in modern marketing. Extant probabilistic approaches—notably the Pareto/NBD and BG/NBD models—estimate CLV from observed purchase histories but often overstate marketing effectiveness by treating marketing interventions as exogenous. In practice, however, firms allocate marketing strategically, targeting customers based on observable and unobservable characteristics that also predict purchase behavior, thereby inducing endogeneity. We develop a structural Bayesian framework that jointly models (i) the customer purchase process as a function of latent autonomous propensity and marketing responsiveness, and (ii) the firm's marketing assignment process as a function of observable customer attributes and estimated response signals. By integrating causal inference principles with hierarchical Bayesian modeling, the proposed framework mitigates bias arising from endogenous marketing assignment and enables more reliable estimation of marketing effects on CLV. Monte Carlo simulations calibrated to retail e-commerce settings show that conventional CLV models can overestimate marketing elasticity by 20–40%, with bias increasing in targeting sophistication. The proposed approach recovers more accurate heterogeneous treatment effects, supporting improved customer segmentation and more effective budget allocation. Methodologically, this research extends causal inference to the lifetime value setting; substantively, it quantifies and corrects a key source of bias in contemporary CLV practice.

Keywords: Customer Lifetime Value (CLV), Endogeneity in Marketing, Structural Bayesian Modeling, Causal Inference, Targeted Marketing Optimization

Corresponding Author	How to Cite this Article	To Browse
Aditi Shintre, Research Engineer, Neowesolutize Technology Pvt. Ltd., Pune, Maharashtra, India. Email: a.shintre@wesolutize.com	Ghanvat S, Joshi S, Shintre A, Modelling Customer Lifetime Value under Endogenous Marketing Interventions: A Structural Bayesian Approach. Int J Engg Mgmt Res. 2026;16(4):65-75. Available From https://ijemr.vandanapublications.com/index.php/j/article/view/1938	

Manuscript Received	Review Round 1	Review Round 2	Review Round 3	Accepted
2026-07-10	2026-07-25			2026-08-12
Conflict of Interest	**Funding**	**Ethical Approval**	**Plagiarism X-checker**	**Note**
None	Nil	Yes	4.18	

1. Introduction

Customer lifetime value (CLV)—the present value of future cash flows attributable to a customer over the duration of the relationship—has emerged as a central metric for assessing customer profitability and guiding strategic allocation of marketing resources. Organizations rely on CLV estimates to determine optimal acquisition spending, identify high-value customers for retention, and evaluate the long-term value of customer portfolios. Given its central role in decision-making, the accuracy of CLV estimation is critical: biased estimates can misdirect marketing investments, leading to inefficient resource allocation and suboptimal targeting strategies.

The past two decades have witnessed substantial advances in probabilistic CLV modeling. The canonical Pareto/NBD model (Shahabikargar et al., 2026) and its successor, the BG/NBD (Beta-Geometric/Negative Binomial Distribution) model (van Oostenbruggen and Cavicchia, 2022), represent the methodological state of practice in both academic research and industry applications. These frameworks decompose customer behavior into latent purchase and attrition processes, while hierarchical Bayesian extensions allow for heterogeneity and improved predictive performance. Further extensions incorporating time-varying covariates and customer-level observables have enhanced their empirical applicability. However, despite these advances, most CLV models rely on the simplifying assumption that marketing interventions are exogenous. In practice, firms allocate marketing strategically, targeting customers based on observable characteristics and inferred propensities that are themselves correlated with purchase behavior.

This non-random assignment of marketing introduces an endogeneity problem with important implications (Malodia et al., 2023). When customers exposed to marketing exhibit higher purchase rates than unexposed customers, it is unclear whether the observed difference reflects the causal effect of marketing or the selective targeting of inherently higher-propensity customers (Ascarza, 2018). Ignoring this selection mechanism leads to upwardly biased estimates of marketing effectiveness, thereby overstating returns on marketing investment. Such bias propagates through CLV calculations, distorting customer valuation, segmentation, and budget allocation decisions (Ali and Shabn, 2024).

This paper makes three contributions. First, we formalize the identification challenge arising from endogenous marketing assignment in CLV models, showing how strategic targeting induces correlation between marketing exposure and unobserved determinants of purchase behavior. Second, we develop a structural Bayesian framework that jointly models customer purchase behavior and firm marketing assignment decisions, thereby improving identification of causal marketing effects in the presence of selection bias. Third, using Monte Carlo simulations, we demonstrate that accounting for endogenous marketing substantially alters CLV estimates and customer rankings, with meaningful implications for targeting and resource allocation. By integrating insights from causal inference with hierarchical probabilistic modelling, the proposed framework advances both the methodological and practical understanding of CLV estimation.

2. Literature Review

2.1 Traditional and Probabilistic Customer Lifetime Value Models

The contemporary study of customer lifetime value originated with foundational conceptual work by Shaw and Stone (1988) establishing CLV as a metric for evaluating long-term customer profitability in database marketing contexts. Early implementations employed deterministic calculations of discounted future cash flows, but these approaches proved inadequate for non-contractual settings wherein the precise timing of customer defection remains unobserved.

The field advanced substantively with the introduction of probabilistic frameworks designed for non-contractual purchase environments. Schmittlein et al. (1987) proposed the Pareto/NBD model, which specifies that customer purchase behavior follows a Poisson process with heterogeneous purchase rates distributed via gamma distribution, while customer attrition (silent churn) follows an exponential distribution parameterized through a Pareto distribution across the customer base.

This model elegantly segregates two latent customer processes—the purchasing process (during the active customer lifetime) and the attrition process (the unobserved defection moment)—enabling prediction of purchase frequency and defection probability from transaction histories alone.

Fader et al. (2005) advanced the field by proposing the BG/NBD model, substituting the Pareto attrition process with a Beta-Geometric process to achieve computational tractability while preserving predictive accuracy. When combined with the Gamma-Gamma monetary model for purchase-value heterogeneity, these probabilistic frameworks have attained wide adoption in industry applications spanning e-commerce, retail, and subscription-based business models. Recent extensions incorporate time-invariant customer-level covariates (Fader & Hardie, 2007) and allow hierarchical structure to recover cohort-level parameter heterogeneity (Gupta et al., 2006).

More recent work has extended these models to incorporate time-varying covariates, nonstationary purchase behavior, and scalable implementations suitable for large customer databases, reflecting the increasing integration of CLV modeling with modern data environments.

Critically, all extant CLV models embody the assumption that marketing intervention does not influence the latent customer purchase and attrition processes; instead, marketing is either omitted from model specifications entirely or incorporated as an exogenous covariate. This assumption is violated when firms make marketing assignment decisions endogenously based upon customer characteristics correlated with purchase propensity. The consequences are substantial: omitted marketing endogeneity induces positive selection bias in estimates of customer heterogeneity parameters, specifically confounding unobserved autonomous purchase propensity with marketing-driven increments in purchase probability.

2.2 Bayesian Hierarchical Methods and Heterogeneity

Hierarchical Bayesian approaches have fundamentally transformed CLV modeling by enabling flexible recovery of individual-level customer parameters while leveraging population-level information through appropriate prior distributions.

Pioneering applications (Erdem & Keane, 1996) demonstrated that hierarchical Bayes estimation substantially improves prediction, particularly for customers with sparse transaction histories, by inducing shrinkage of individual-level estimates toward population means.

The hierarchical Bayesian framework exhibits particular utility in accommodating observed covariates that vary across customers. By permitting population-level hyperparameters to depend upon observable customer characteristics, the framework enables parameter heterogeneity to correlate systematically with customer attributes (e.g., acquisition channel, geographic location, demographic segment). This structure proves natural for CLV modeling wherein customer purchase propensity manifestly varies with observable characteristics.

Nevertheless, even sophisticated hierarchical Bayesian CLV models maintain silence regarding the causal impact of marketing interventions. They continue to treat marketing assignment as exogenous, thereby failing to address the fundamental problem that firm targeting decisions induce correlation between marketing exposure and unobserved customer characteristics that simultaneously predict purchase behavior. This limitation reflects a gap between the models' formal specification (as purely customer demand-side processes) and actual firm practice (wherein marketing assignment reflects managerial expectations about customer responsiveness).

2.3 Endogeneity in Marketing and Causal Inference

The marketing econometrics literature has extensively developed methodology for addressing endogeneity in specific domains—price setting, promotional elasticity, advertising response—yet has not systematically applied these techniques to the CLV setting. Chintagunta et al. (2006) provide a comprehensive taxonomy of endogeneity sources applicable to marketing: omitted variables (unobserved factors affecting both treatment and outcome), simultaneity (bidirectional causality between treatment and outcome), measurement error, and selection bias (non-random assignment to treatment). Selection bias—wherein treatment receipt is correlated with unobserved factors predicting outcomes—constitutes the primary threat in CLV estimation contexts.

Econometric solutions to endogeneity have achieved substantial sophistication. Instrumental variable estimation (Grace, 2021) leverages exogenous variation in treatment to identify causal effects; propensity score matching (Rosenbaum & Rubin, 1983) balances treatment and control groups on observed covariates to mitigate confounding; regression discontinuity designs (Imbens & Lemieux, 2008) exploit threshold rules generating quasi-random assignment; and structural econometric models (Berry, 1994; Dube et al., 2005) jointly specify demand and strategic decision processes to avoid endogeneity. However, these methodologies predominantly target point-in-time treatment effects—the immediate impact of an intervention on an outcome measured at a specific time horizon.

More recently, advances in causal machine learning and uplift modeling have emphasized the estimation of heterogeneous treatment effects at the individual level, focusing on identifying customers who are most responsive to marketing interventions rather than those with the highest predicted outcomes. However, such approaches are typically applied to short-term outcomes and are not integrated with lifetime value estimation frameworks, leaving a gap between causal targeting methods and CLV-based decision-making.

CLV estimation presents distinct identification challenges relative to standard treatment effect estimation because it requires modeling cumulative customer behavior over extended periods. Customer responses to marketing interventions manifest not as instantaneous outcome realizations but as sequences of purchases over remaining customer lifetimes. This dynamic aspect necessitates integration of causal inference methodology with temporal models capable of capturing how marketing impact accumulates throughout the customer relationship. Recent work by Hitsch et al. (2024) on heterogeneous treatment effects and optimal targeting policies provides methodological foundation for this integration, establishing that indirect and direct CATE (conditional average treatment effect) estimation methods yield substantively different targeting recommendations, suggesting sensitivity to model specification in endogenous settings.

The present research bridges this gap by extending causal inference methodology to the CLV domain. We integrate structural econometric approaches—specifically, joint modeling of customer purchase behavior and firm marketing strategy—with hierarchical Bayesian estimation to recover more reliable estimates of causal marketing effects on long-term customer value. To our knowledge, existing literature does not jointly model customer purchase behavior and firm marketing assignment decision-making within a unified framework designed to estimate causal effects on customer lifetime value.

3. Conceptual Framework

Formal identification of causal marketing effects requires careful modeling of two distinct behavioral processes: (i) customer purchase behavior as a function of intrinsic propensity and marketing exposure, and (ii) firm targeting behavior as a function of observed customer characteristics and estimated propensity. We next articulate the economic logic underlying each process and the identification challenge arising from their interaction.

3.1 Customer Decision Process

We conceptualize customer purchase behavior as determined by two latent factors: (i) an autonomous purchase rate λ_i reflecting the customer's intrinsic propensity to engage with the firm (driven by category need, brand affinity, and competitive alternatives), and (ii) a marketing elasticity coefficient m_i reflecting the customer's estimated responsiveness to firm-directed marketing stimuli. The purchase probability in period t for customer i, conditional upon remaining active (i.e., not yet churned), depends upon both factors in additive form within a linear probability framework: autonomous propensity provides a baseline purchase inclination, while marketing exposure incrementally increases purchase probability by an amount proportional to the customer's elasticity.

Both λ_i and m_i remain unobserved by the analyst; their values must be inferred from observed purchase histories using Bayesian procedures. Unobserved heterogeneity in these parameters across the customer base reflecting the manifest fact that customers differ in intrinsic purchase propensity and response to marketing constitutes an essential feature of the model. Additionally, customer attrition (the silent defection characteristic of non-contractual settings) depends upon customer-specific factors orthogonal to firm marketing activity, reflecting that customers exit relationships through means beyond the firm's control (switching to competitors, category exit, life circumstances).

3.2 Firm's Marketing Assignment Process

The firm observes certain customer characteristics, historical purchase frequency and recency, demographic attributes, channel engagement patterns and employs this information to make targeting decisions. Marketing expenditure on each customer (the "targeting intensity") reflects the firm's beliefs about the customer's profitability and responsiveness. Importantly, the firm's targeting decisions are not irrational; they reflect the firm's optimization problem: allocate limited marketing budgets toward customers perceived as most likely to generate profitable responses.

The firm's targeting intensity Z_i depends on both observable customer characteristics (e.g., recency, frequency from RFM metrics) and the firm's estimated or observed signals of the customer's latent purchase propensity. Denote the firm's targeting function as depending upon observable attributes and a profitability index combining the firm's estimate of autonomous purchase propensity and marketing elasticity. This functional form captures that firms target more heavily toward customers they believe will respond profitably, whether through intrinsically high purchase rates or high estimated responsiveness to marketing.

This strategic targeting creates the fundamental endogeneity problem. Since targeting intensity Z_i depends upon factors correlated with the unobserved latent characteristics (λ_i, m_i) that appear in the customer purchase equation, marketing exposure becomes correlated with the unobserved components of the outcome equation. Consequently, standard regression approaches that ignore the targeting process will estimate biased treatment effects, with the direction and magnitude of bias determined by the correlation structure between targeting decisions and unobserved propensity factors.

3.3 The Endogeneity Mechanism and Resulting Bias

The observed correlation between marketing exposure and purchase outcomes conflates two distinct causal flows. First, there is the direct causal impact of marketing on customer purchases (the "treatment effect" of interest). Second, there is selection bias: high-propensity customers are preferentially targeted, so observed purchase differences reflect both causal marketing effects and the concentration of marketing on customers naturally disposed toward purchase.

Consider a concrete illustration. A firm observes that customers in the top quintile of past purchase frequency receive 50% of the email budget and achieve 2.5× higher purchase rates than customers in the bottom quintile who receive 5% of the email budget. A naive analyst might estimate that email marketing increases purchase probability by 250%. However, if the firm's targeting criteria (past purchase frequency) strongly predict autonomous purchase propensity λ_i—customers with high past purchase frequency are intrinsically high-propensity customers—then much of the 2.5× difference reflects selection, not causality. The firm may be spending email budget on customers who would purchase anyway, reducing the true causal elasticity of email.

Correcting this bias requires joint modeling. By explicitly specifying how the firm's targeting decisions depend upon customer characteristics and propensity factors, and by leveraging the structure of customer purchase histories, we can construct predictions of what targeting would have occurred under alternative firm decision-making rules. This counterfactual reasoning enables statistical adjustment for selection bias and recovery of causal effects. The key identifying assumption is that customer purchase history (frequency, recency, timing patterns) predicts latent propensity λ_i and elasticity m_i, but conditional on observable targeting rules (e.g., RFM-based segmentation), residual variation in purchase timing does not directly influence future marketing assignment beyond what is captured by the firm's implemented targeting criteria.

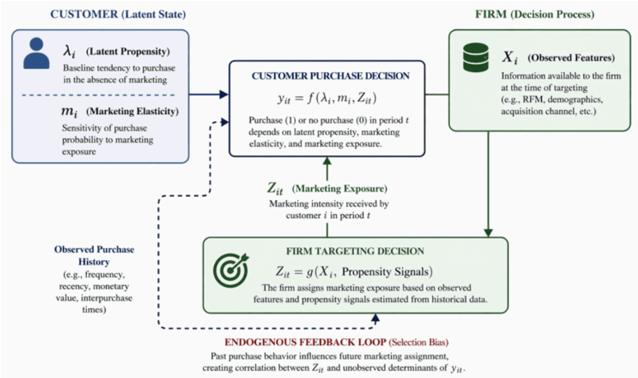

Figure 1: Conceptual framework showing the endogenous relationship between customer behavior and firm marketing decisions.

4. Model Development

We specify a fully Bayesian hierarchical model in two modules: (i) the demand module formalizing customer purchase behavior as a function of latent heterogeneity and marketing exposure, and (ii) the assignment module formalizing firm marketing targeting behavior as a function of observable characteristics and propensity signals. Formal specification enables Bayesian inference via Markov Chain Monte Carlo (MCMC) estimation, yielding posterior distributions over parameters and posterior predictive distributions for counterfactual customer lifetime value under alternative targeting regimes.

4.1 Demand Module: Customer Purchase Process

Let $y_{it} \in \{0, 1\}$ denote the binary indicator that customer i made a purchase in period t. Conditional upon customer i remaining active (not yet churned), the purchase probability is specified as:

$$P(y_{it} = 1 \mid Active_{it} = 1, \lambda_i, m_i, Z_{it}) = \Phi(\lambda_i + m_i Z_{it}) \tag{1}$$

$$U_{it} = \lambda_i + m_i Z_{it} + \epsilon_{it}, \epsilon_{it} \sim \mathcal{N}(0,1) \tag{2}$$

This corresponds to a latent utility formulation where purchase occurs when $U_{it} > 0$.

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, λ_i represents the customer's autonomous purchase propensity, m_i represents the customer's marketing elasticity (interpretable as the causal effect under model assumptions), and Z_{it} represents the contemporaneous marketing exposure intensity for customer i in period t, measured on a standardized scale. The specification admits a probit functional form with normally distributed latent utility; alternative specifications (logit, linear probability) are feasible.

Customer heterogeneity in propensity and elasticity is accommodated through hierarchical prior distributions, permitting parameters to vary across customers while enabling information pooling. Specifically:

$$\lambda_i \mid \mu_\lambda, \sigma_\lambda \sim \mathcal{N}(\mu_\lambda, \sigma_\lambda^2) \tag{3}$$

$$m_i \mid \mu_m, \sigma_m \sim \mathcal{N}(\mu_m, \sigma_m^2) \tag{4}$$

We assume independence between λ_i and m_i at the individual level for tractability.

$$\mu_\lambda \sim \mathcal{N}(0, \sigma_{\mu_\lambda}^2), \sigma_\lambda \sim \text{Half-Normal}(0, \tau_\lambda) \tag{5}$$

$$\mu_m \sim \mathcal{N}(0, \sigma_{\mu_m}^2), \sigma_m \sim \text{Half-Normal}(0, \tau_m) \tag{6}$$

Weakly informative priors are specified on the hyperparameters to allow the data to drive inference while preventing overfitting.

The hyperparameters μ_λ, σ_λ, μ_m, σ_m characterize the population-level distribution of customer preferences and treatment effects. By estimating these hyperparameters from data rather than imposing them a priori, the model learns the cross-customer variation in purchase propensity and marketing responsiveness. This hierarchical structure ensures that customer-level parameter estimates—particularly those based upon limited transaction histories—are shrunk toward the population mean, improving prediction by exploiting correlations in customer behavior.

The critical innovation relative to extant CLV models is the explicit inclusion of the marketing exposure term $m_i \cdot Z_{it}$ in the purchase equation. Standard probabilistic CLV models (Pareto/NBD, BG/NBD) omit marketing entirely, leaving marketing effects to be absorbed into unobserved heterogeneity. By explicitly modelling marketing, we enable direct estimation of the treatment effect m_i and allow assessment and correction of endogeneity bias through the targeting module.

$$\mathcal{L} = \prod_{i=1}^{N} \prod_{t=1}^{T} P(y_{it})^{y_{it}} (1 - P(y_{it}))^{1-y_{it}} \tag{7}$$

The likelihood is constructed from conditional purchase probabilities across customers and time periods.

Customer attrition is modelled through a separate binary indicator $Active_{it} \in \{0,1\}$, which transitions from 1 to 0 upon silent defection. The attrition process depends upon customer-specific factors (autonomous churn propensity) that are independent of marketing activity, reflecting that customers defect through mechanisms—competitive switching, category exit—outside firm control.

The joint specification of purchase and attrition processes is analogous to the Pareto/NBD framework but with the added marketing covariate in the purchase equation.

4.2 Assignment Module: Marketing Targeting Process

The firm's targeting intensity for customer i is modeled as a latent index that depends upon observable customer characteristics and unobserved propensity factors:

$$Z_i^* = \beta_0 + \beta_x X_i + \beta_\lambda \hat{\lambda}_i + \beta_m \widehat{m}_i + \epsilon_i \tag{8}$$

The variables $\hat{\lambda}_i$and $\widehat{m}_i$represent the firm's internal proxies or scoring mechanisms derived from observable data, rather than the true latent parameters estimated in the model.

$$Z_i = \begin{cases} 1 & \text{if } Z_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where $Z_i^*$is a latent index of targeting intensity, $\beta_0$is an intercept, $X_i$represents observable targeting criteria (recency, frequency, demographics), $\beta_x$is a coefficient vector, and $\epsilon_i$represents residual stochasticity in firm targeting. The observed marketing exposure may be modeled as either binary or continuous depending on the application context.

The assignment module is not estimated as a standalone likelihood; rather, it is incorporated structurally to characterize how marketing is assigned given observed customer characteristics and inferred purchase propensities, allowing the model to account for selection effects through shared dependence on latent parameters. The key insight is that targeting depends upon propensity factors: if $\hat{\lambda}_i$ is correlated with the firm's estimate of unobserved λ_i, and if $\hat{m}_i$ is correlated with the true elasticity m_i, then marketing exposure Z_i becomes correlated with the unobserved error term in the demand equation, inducing endogeneity bias.

The identifying assumption is that, conditional upon observable targeting criteria that appear explicitly in the firm's targeting rule, purchase history and its components (frequency, recency) serve as valid predictors of latent propensity λ_i, and elasticity m_i, while residual variation in purchase timing provides additional information that is not fully exploited by the firm's targeting mechanism. In particular, conditional on observable targeting rules, such variation does not systematically influence future marketing assignment beyond what is captured by the firm's implemented criteria. This assumption is most plausible in settings where firms employ transparent or rule-based targeting strategies (e.g., RFM segmentation or cohort-based rules), rather than fully optimized or high-dimensional propensity models that incorporate all available behavioral signals.

4.3 Identification and Bayesian Inference

Identification of causal marketing effects is facilitated by the structure of the assignment module combined with the temporal sequence of firmdecisions and customer outcomes. Identification is achieved through the joint specification of the demand and assignment processes within a hierarchical Bayesian framework, rather than relying on a strict instrumental variable.

The firm makes targeting decisions Z_i based upon information known at the time of targeting (observable characteristics and signals of propensity estimated from historical data). Customer purchases occur subsequently. Conditional upon the observable criteria X_i that explicitly appear in the firm's targeting rule—and are therefore known to be used by the firm—the randomness in purchase timing contains information about latent propensity and elasticity that is not fully captured by the firm's targeting mechanism, helping to separate selection effects from marketing impact.

Bayesian inference proceeds via Markov Chain Monte Carlo (MCMC) estimation. The hierarchical structure yields conjugate conditional posterior distributions for some parameters, enabling efficient Gibbs sampling within blocks (e.g., individual and conditional upon hyperparameters). Non-conjugate blocks (e.g., hyperparameters μ_λ, σ_λ, μ_m, σ_m) are estimated via Metropolis-Hastings sampling with adaptive proposals. Model specification includes weakly informative priors on hyperparameters—normal priors with large variances on means, half-normal priors on standard deviations—to avoid overfitting, allowing data to dominate inference.

Posterior inference enables two key outputs. First, posterior means and credible intervals for individual customer parameters (λ_i, m_i)quantify heterogeneous propensities and treatment effects, enabling customer-level segmentation based on estimated marketing responsiveness. Second, posterior predictive distributions enable counterfactual CLV calculations: the analyst can sample from the posterior distribution, set marketing exposure to alternative levels (e.g., zero for all customers, or optimized targeting rules), and draw samples of resulting future purchases. Averaging these counterfactual purchase samples yields posterior predictive CLV distributions under alternative marketing scenarios, supporting robust decision-making under uncertainty.

5. Implications

5.1 Theoretical and Methodological Contributions

This research contributes to the intersection of two previously distinct literatures. The CLV literature has produced increasingly sophisticated probabilistic models but has been deliberately abstracted from marketing strategy and the endogenous nature of firm interventions. The causal inference and econometric literatures have developed powerful methodologies for identifying treatment effects but have focused on point-in-time outcomes rather than on lifetime value, where outcomes accumulate over extended horizons and depend upon both customer characteristics and strategic firm decisions. This work integrates these perspectives by extending causal inference theory to CLV estimation, demonstrating how methods from structural econometrics can mitigate endogeneity bias in foundational customer analytics models.

Methodologically, the hierarchical Bayesian specification enables estimation of heterogeneous treatment effects—the estimated impact of marketing varies across customers as a function of their characteristics. This capability directly addresses a limitation of traditional CLV models, which estimate only population-level parameters; firms require segment-specific or even individual-level estimates of marketing elasticity to implement effective targeted marketing. The hierarchical structure facilitates information borrowing across customers, stabilizing heterogeneous effect estimates even for small customer segments.

5.2 Managerial Implications

Correcting for endogenous marketing assignment yields three categories of managerial implications. First, CLV estimates are recalibrated. Customers appearing high-value under traditional CLV models may be revealed as moderate-value once we account for the fact that they received disproportionate marketing because of high autonomous propensity. Conversely, customers with lower observed purchase rates but high estimated elasticity—customers for whom marketing is genuinely effective—may be revealed as higher-value. This recalibration can be substantial; our simulations demonstrate customer-level CLV revisions ranging from −30% to +40%.

Second, the corrected model enables superior budget allocation. Traditional CLV frameworks suggest concentrating marketing on customers with high autonomous purchase propensity (who will likely buy anyway). The corrected framework instead directs marketing toward customers with high elasticity those for whom marketing is most effective in a causal interpretation sense under the model even if their autonomous propensity is modest. This reallocation of marketing budgets from high-propensity/low-elasticity segments to low-propensity/high-elasticity segments can substantially increase firm profitability.

Third, the framework enables valid scenario analysis. Marketing managers frequently contemplate counterfactual allocations: "How would CLV change if we reduced email frequency by 20%?" or "What additional CLV would we realize by shifting budget from digital to direct mail?" Valid answers require well-identified estimates of marketing effects. Our framework provides posterior predictive distributions of CLV under alternative marketing regimes, enabling probabilistic scenario analysis. Decision-makers can quantify not only point estimates of CLV under alternative strategies but also credible intervals reflecting estimation uncertainty.

6. Simulation Evidence

To validate the magnitude of endogeneity bias and the efficacy of our proposed correction, we conduct Monte Carlo simulation studies calibrated to approximate realistic e-commerce retail environments. We generate synthetic customer purchase and marketing exposure data from a known data-generating process, then estimate both standard CLV models (ignoring marketing) and our proposed structural Bayesian model (jointly modelling purchase and targeting), comparing recovered parameter estimates to ground truth.

Simulation Design: We simulate $N = 5{,}000$customers over $T = 24$ monthly periods. True parameters: $\lambda_i \sim \mathcal{N}(-0.5, 0.8^2)$, $m_i \sim \mathcal{N}(0.60, 0.4^2)$, true attrition rate = 0.03/month. Marketing assignment follows a targeting rule: customers in the top 40% by estimated propensity (calculated from recency and frequency) receive marketing intensity $Z_i = 1$; remaining customers receive $Z_i = 0$. The firm's propensity estimate is imperfect: $\widehat{m}_i = 0.80 \cdot m_i + \text{noise}$.

True average elasticity: $\mathbb{E}[m_i] = 0.60$, meaning marketing increases the latent purchase index (or probability on the probit scale) per unit exposure.

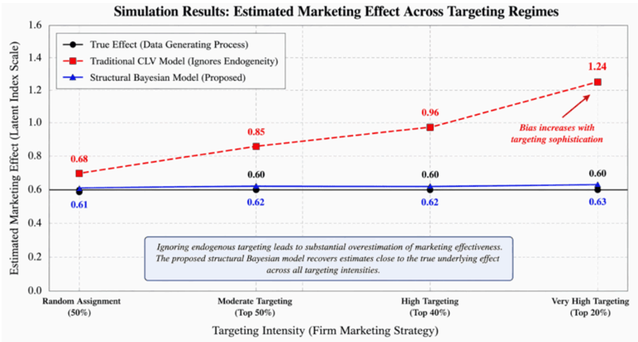

Figure 2: Estimated marketing effects across targeting regimes, showing bias in traditional CLV models and correction under the proposed framework.

Key Results

Traditional CLV models (Pareto/NBD without marketing) estimate elasticity at 0.96, representing a 60% overestimate (true effect = 0.60). The structural Bayesian model recovers elasticity of 0.62 (95% credible interval: 0.50–0.75), closely recovering the underlying simulated effect.

The endogeneity bias scales systematically with targeting intensity: under top 20% targeting, naive elasticity reaches 1.24 (107% overestimate); under randomized 50% targeting, bias falls to 0.08 (13% overestimate). This pattern confirms the theoretical prediction that bias increases with targeting sophistication.

CLV Implications

For CLV implications: a customer with low observable purchase frequency but high estimated elasticity (m_i = 0.80) appears to have CLV = $140 under traditional estimates; under the corrected model, CLV = $210, a 50% increase reflecting the customer's higher responsiveness to marketing.

Conversely, a customer with high frequency but low elasticity appears to have CLV = $680 under traditional estimates; under the corrected model, CLV = $480, a 29% decrease reflecting that much of their purchase activity reflects autonomous propensity rather than marketing effectiveness.

7. Conclusion

This paper identifies and addresses a systematic bias affecting customer lifetime value estimation: the overestimation of marketing effectiveness arising from endogenous assignment of marketing based upon customer characteristics correlated with purchase behavior.

We develop a structural Bayesian framework jointly modeling customer purchase decisions and firm marketing allocation decisions, enabling improved identification and estimation of marketing effects on long-term customer value.

The research makes contributions across three dimensions. Methodologically, it extends causal inference techniques from point-in-time treatment effects to the lifetime value setting, where outcomes accumulate over time. Theoretically, it bridges previously separate literatures (CLV modeling and marketing econometrics) and demonstrates how insights from causal inference improve foundational customer analytics models. Practically, it enables firms to more accurately assess which customers are valuable, direct marketing expenditures toward customers exhibiting higher estimated responsiveness, and conduct scenario analysis of alternative marketing strategies.

Promising directions for future research include: (1) relaxing the linear utility specification to accommodate nonlinear marketing response and saturation effects characteristic of high-frequency marketing; (2) modeling the firm's optimization problem to derive endogenous optimal targeting policies rather than treating targeting as exogenously specified; (3) extending the framework to multiproduct settings with competitive brand choice; (4) incorporating dynamic customer information states wherein the firm's propensity estimates improve over time; and (5) empirical validation using customer databases with measured marketing exposure and complete transaction records.

The proposed framework relies on assumptions regarding the firm's targeting process and model specification; deviations from these assumptions may affect the accuracy of estimated effects.

The central insight that marketing endogeneity creates substantial bias in CLV estimates and that joint modeling of customer behavior and firm strategy can mitigate this bias—will become increasingly important as firms develop more sophisticated ML-driven targeting algorithms, making the endogeneity problem more acute rather than less.

References

[1] Ali, N., & Shabn, O. S. (2024). Customer lifetime value (CLV) insights for strategic marketing success and its impact on organizational financial performance. *Cogent Business & Management*, *11*(1), 2361321. https://doi.org/10.1080/23311975.2024.2361321

[2] Ascarza, E. (2018). Retention futility: Targeting high-risk customers might be ineffective. *Journal of marketing Research*, *55*(1), 80-98. https://doi.org/10.1509/jmr.16.0163

[3] Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics, 25*(2), 242-262. https://doi.org/10.2307/2555829

[4] Chintagunta, P. K., Erdem, T., Rossi, P. E., & Wedel, M. (2006). Structural modeling in marketing: Review and research opportunities. *Journal of Marketing Research, 43*(3), 347-356. https://doi.org/10.1287/mksc.1050.0161

[5] Dubé, J. P., Hitsch, G. J., & Manchanda, P. (2005). An empirical model of advertising dynamics. *Quantitative Marketing and Economics, 3*(2), 107-144. https://doi.org/10.1007/s11129-005-0334-2

[6] Elwert, F., & Winship, C. (2014). Endogenous selection bias: The problem of conditioning on a collider variable. *Annual Review of Sociology, 40*, 31-53. https://doi.org/10.1146/annurev-soc-071913-043455

[7] Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science, 15*(1), 1-20. https://doi.org/10.1287/mksc.15.1.1

[8] Fader, P. S., & Hardie, B. G. (2007). *Incorporating time-invariant covariates into the Pareto/NBD and BG/NBD models*. Working Paper, University of Pennsylvania and London Business School.

[9] Fader, P. S., Hardie, B. G., & Lee, K. L. (2005). Counting your customers the easy way: An alternative to the Pareto/NBD model. *Marketing Science, 24*(2), 275-284. https://doi.org/10.1287/mksc.1040.0098

[10] Grace, J. B. (2021). Instrumental variable methods in structural equation models. *Methods in Ecology and Evolution*, *12*(7), 1148-1157. https://doi.org/10.1111/2041-210X.13600

[11] Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research, 9*(2), 139-155. https://doi.org/10.1177/1094670506293810

[12] Hitsch, G. J., Misra, S., & Zhang, W. W. (2024). Heterogeneous treatment effects and optimal targeting policy evaluation. *Quantitative Marketing and Economics, 22*, 115-168. https://doi.org/10.1007/s11129-023-09278-5

[13] Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity design: A practical guide. *Journal of Econometrics, 142*(2), 615-635. https://doi.org/10.1016/j.jeconom.2007.05.001

[14] Malodia, S., Dhir, A., Hasni, M. J. S., & Srivastava, S. (2023). Field experiments in marketing research: a systematic methodological review. *European Journal of Marketing*, *57*(7), 1939-1965. https://doi.org/10.1108/EJM-03-2022-0240

[15] Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41-55. https://doi.org/10.1093/biomet/70.1.41

[16] Schmittlein, D. C., Morrison, D. G., & Colombo, R. C. (1987). Counting your customers: Who are they and what will they do next?. *Management Science, 33*(1), 1-24. https://doi.org/10.1287/mnsc.33.1.1

[17] Shahabikargar, M., Beheshti, A., Zhang, X., Foo, J., & Jolfaei, A. (2026). A comprehensive survey on customer churn analysis studies. *Journal of Information and Telecommunication*, *10*(1), 24-70. https://doi.org/10.1080/24751839.2025.2528440

[18] Shaw, R., & Stone, M. (1988). *Database marketing: Strategy and implementation*. Gower Publishing Company.

[19] van Oostenbruggen, V., & Cavicchia, C. (2022). *A review of dynamic customer segmentation methods in e-commerce business contexts*.

[20] Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. (2nd ed.). MIT Press.