Customer Lifetime Value as a Decision-Centric Optimization Problem under Uncertainty

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Abstract

Customer Lifetime Value (CLV) is widely used to guide retention and targeting strategies. However, most existing approaches treat CLV as a static prediction problem, ignoring temporal dynamics, uncertainty in churn behavior, and the impact of managerial actions. This paper proposes a decision-centric CLV framework in which customer value is modeled as a function of survival dynamics, conditional revenue generation, and intervention policies under budget constraints.

Using a large-scale non-contractual retail dataset containing over one million transactions, we construct a research-grade transaction timeline, derive time-causal customer state representations, model latent churn through discrete-time hazard estimation, and compute expected discounted lifetime value. We then formulate CLV-based targeting as a constrained optimization problem and evaluate policies using counterfactual uplift modeling.

Results demonstrate that prediction accuracy alone is insufficient for decision quality. Sensitivity analysis reveals significant inflation risk under optimistic survival assumptions, and policy-level evaluation shows that uplift-aware targeting outperforms heuristic strategies under heterogeneous treatment effects.

The findings emphasize that CLV should be treated as a sequential decision variable rather than a predictive score.

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1. Introduction

Customer Lifetime Value (CLV) plays a central role in modern customer relationship management, marketing resource allocation, and retention strategy. Organizations routinely rank customers by predicted CLV to prioritize targeting decisions. However, conventional CLV frameworks exhibit three critical limitations:

1. They treat CLV as a static regression problem.
2. They assume deterministic churn identification.
3. They ignore the effect of managerial interventions on future customer trajectories.

In practice, customer behavior is non-stationary, churn is latent and partially observable, and business actions alter future outcomes. Therefore, CLV must be reframed as a dynamic decision problem under uncertainty.

This paper introduces a decision-centric CLV framework that integrates survival modeling, expected value estimation, counterfactual uplift analysis, and budget-constrained optimization. Rather than optimizing prediction accuracy, the objective is to optimize business decisions.

Contributions

This study makes three primary contributions:

1. It formulates CLV as a sequential decision problem integrating churn risk, expected revenue, and action-dependent value.
2. It demonstrates policy-level evaluation using counterfactual uplift modeling.
3. It provides robustness analysis highlighting inflation risks and failure regimes.

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2. Research Problem Formulation

We define the research problem as follows:

How can Customer Lifetime Value be estimated, updated, and optimized when:

- Customer behavior is non-stationary,
- Churn is uncertain and partially observable,
- Business actions influence future trajectories,
- Decisions must satisfy budget and risk constraints?

Let each customer be represented by a dynamic state vector s_t.
Let action $a_t \in \{0,1\}$represent whether a retention intervention is applied.

The objective is:

Maximize expected incremental lifetime value subject to budget constraints.

This formulation shifts CLV from prediction to optimization.

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3. Data & Transaction Timeline Construction

The empirical analysis uses the Online Retail II dataset (~1.06 million transactions). Phase 1 constructs a research-grade transaction timeline with strict cleaning rules

CLV4_Phase1_Data_Timeline

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- Removal of missing customer identifiers.
- Proper datetime conversion.

- Explicit cancellation handling.
- Temporal sorting by customer and invoice.

An event index ensures monotonic transaction ordering per customer.

This prevents temporal leakage and establishes a causal data foundation.

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4. Customer State Representation

Phase 2 constructs time-causal customer states

CLV4_Phase2_Customer_State

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For each invoice, state variables are computed using only historical information:

- Recency (days since last purchase)
- Frequency (cumulative purchases)
- Monetary average
- Revenue change
- Recency change

Current transaction revenue is excluded from its own state to prevent leakage.

This produces a dynamic behavioral trajectory representation.

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5. Latent Churn & Survival Modeling

In non-contractual settings, churn is unobserved. Phase 3 defines churn using an inactivity threshold of 180 days

PHASE_3_Latent_Churn_&_Survival…

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Phase 4 applies discrete-time survival modeling

PHASE_4_Hazard_Modeling_Time_De…

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- Continuous duration is discretized into monthly bins.
- A person-period dataset is constructed.

- Logistic regression estimates hazard probability:

$P(event_t = 1$
$\mid survival\ u \qquad p\ t \qquad o\ t$

Survival probability is derived via cumulative product:

$$S(t) = \prod_{k=1}^{t} (1 - h_k)$$

This captures uncertainty in churn timing.

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6. Expected CLV Estimation

Phase 5 computes expected discounted lifetime value

PHASE_5_Expected_Survival_×_Con…

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Expected CLV per customer:

$$CLV = \sum_{t=0}^{H} S(t) \cdot E[R_t \mid alive] \cdot \gamma^t$$

Where:

- $S(t)$= survival probability
- $E[R_t]$= expected conditional revenue
- γ= discount factor

Aggregation produces customer-level expected CLV.

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7. Decision Optimization

Phase 6 formulates CLV targeting as an optimization problem

PHASE_6_Decision_Optimization_B…

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Assumptions:

- Action cost = 100
- Total budget = 50,000
- Max customers targeted = 500

Incremental CLV is estimated as a proportional uplift.
Risk control is applied via 95th percentile capping.

Customers are ranked by capped incremental CLV.

Objective:

Maximize total incremental CLV under budget constraint.

This converts CLV from metric to decision tool.

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8. Counterfactual Uplift & Policy Evaluation

Phase 7 introduces heterogeneous treatment effects

PHASE_7_Counterfactual_Uplift_&…

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Synthetic treatment assignment simulates:

- Higher benefit for high-recency, low-frequency customers.
- Random noise to mimic real-world uncertainty.

Policy comparison shows:

- CLV-only targeting is suboptimal under heterogeneity.
- Uplift-aware targeting improves total expected gain.

This validates the necessity of counterfactual reasoning.

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9. Failure Modes & Sensitivity Analysis

Phase 8 stress-tests assumptions

PHASE_8_Failure_Modes,_Sensitiv…

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9.1 CLV Inflation

Changing discount rate and horizon significantly alters total CLV.

Optimistic assumptions inflate value estimates, potentially leading to over-investment.

9.2 Heuristic Dominance

When treatment effects are homogeneous, simple ranking performs comparably.

This highlights the conditional value of advanced modeling.

9.3 Behavioral Regime Shifts

Survival assumptions may break under structural change.

Robust monitoring is required.

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10. Discussion

This study demonstrates that CLV should be treated as a decision variable.

Key insights:

- Survival modeling quantifies uncertainty.
- Optimization ensures budget discipline.
- Uplift modeling prevents misallocation.
- Sensitivity analysis protects against inflation.

Prediction accuracy alone does not guarantee optimal decisions.

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11. Limitations & Future Work

Limitations include:

- Synthetic uplift estimation.
- Single-action framework.
- Static policy cycle.

Future extensions:

- Real randomized intervention data.
- Multi-action policy optimization.
- Dynamic policies using reinforcement learning.
- Robust optimization under distribution shift.

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12. Conclusion

Customer Lifetime Value is not merely a predictive metric.
It is a decision problem under uncertainty.

By integrating survival dynamics, expected value modeling, counterfactual evaluation, and constrained optimization, this framework provides a principled approach to long-horizon customer value management.