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Article

## A Dynamic User Value Evaluation Model and Intelligent Recommendation Mechanism for Precision Marketing

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**Abstract:** Live-stream commerce, characterized by real-time user-host interactions and rapidly shifting purchase intent, highlights the critical limitations of traditional static customer valuation models such as Recency, Frequency, Monetary (RFM) analysis. These conventional models, alongside standard recommendation engines optimized solely for short-term engagement metrics, fundamentally fail to capture dynamic user value trajectories and often misclassify behaviorally active but historically low-spend users. To comprehensively address this significant research gap, this study proposes a novel closed-loop, co-adaptive framework integrating a Dynamic User Value Evaluator (DUVE) and an Intelligent Recommendation Agent (IRA). Specifically, the DUVE module updates user embeddings every 15 minutes using an advanced temporal graph neural network equipped with attention-based decay mechanisms, ensuring highly accurate temporal representations. Concurrently, the IRA employs a sophisticated dual-objective deep Q-network designed to optimally balance immediate conversion rates with long-term customer lifetime value. Evaluated via a rigorous 28-day large-scale A/B test deployed on a major live-commerce platform, the proposed full system significantly outperformed the static baseline. It achieved an impressive 11.9% increase in Gross Merchandise Volume (GMV) per impression and an 18.9% higher capture rate of high-value users. Furthermore, the framework successfully raised 30-day user retention from 12.1% to 14.4% and increased the average order value by 6.2%. The empirical findings conclusively demonstrate that synchronizing real-time value assessment with adaptive recommendation strategies enables substantially more effective, profitable, and sustainable precision marketing within highly dynamic digital retail environments.

**Keywords:** user value evaluation; intelligent recommendation; live commerce; adaptive systems; precision marketing

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### 1. Introduction

The rise of real-time digital commerce has exposed critical limitations in traditional customer valuation methods. In live-streaming shopping, a dominant format in China's e-commerce landscape, user intent shifts within minutes under the influence of social cues, limited-time offers, and host interactions. Static models based on historical transactions, such as Recency-Frequency-Monetary (RFM) analysis, fail to capture these dynamics. For instance, during Alibaba's 2024 Singles' Day festival on Taobao Live, many users exhibited high engagement, commenting, gifting, sharing streams, and adding items to carts, without immediate purchases. One verified case involved a user who interacted extensively with a premium skincare broadcast but bought nothing during the session; she returned independently 48 hours later to complete a ¥1,850 purchase [1]. Legacy systems labeled her "low-value" due to past inactivity and excluded her from follow-up campaigns, missing a high-intent opportunity.

This disconnect stems from a structural gap in current marketing architectures: user evaluation and recommendation operate in silos. Recommendation engines optimize for short-term metrics like click-through rate or watch time, while value assessment relies on lagging financial indicators. The two systems rarely exchange signals, leading to inefficient targeting. A 2023 internal audit by a major Chinese e-commerce platform revealed that over 37% of users who made high-value purchases within seven days of a live session had been classified as "low-priority" by static CLV models because they lacked recent transaction history. Such misclassification results in wasted inventory exposure on low-yield users and underinvestment in behaviorally active but historically quiet segments [2].

Recent advances in machine learning have begun to address this, yet practical implementations remain constrained. Reinforcement learning frameworks can model sequential decisions but often prioritize immediate conversion, especially during high-pressure sales events like Double Eleven. Moreover, most models treat all user actions as equally informative, ignoring temporal decay, e.g., a comment made 30 seconds ago carries more predictive power than one from an hour prior [1]. Without time-aware behavioral encoding, even sophisticated algorithms miss the rhythm of real-time intent.

To bridge this gap, this study develops an integrated mechanism that dynamically evaluates user value through fine-grained, time-stamped interactions and feeds this assessment directly into the recommendation engine [1]. Using anonymized session logs from Taobao Live (September 2024-February 2025), a dataset validated in public technical reports by Alibaba Cloud, the model updates user embeddings every 15 minutes based on live behaviors. By aligning real-time engagement signals with long-term value estimation, the framework enables precision marketing that is both responsive and strategic, moving beyond retrospective segmentation toward anticipatory personalization.

## 2. Literature Review

The academic and industrial discourse on precision marketing has long been bifurcated into two parallel streams: customer value assessment and intelligent recommendation [2]. While both have advanced significantly in technical sophistication, their conceptual and operational separation has produced a systemic blind spot, one that privileges measurement over meaning and prediction over purpose.

Customer value models, from classical RFM to modern probabilistic CLV frameworks, treat users as passive data sources whose worth is reducible to past transactions. Even recent deep learning extensions, such as recurrent neural networks trained on purchase sequences, remain fundamentally retrospective. They assume stationarity in user preferences, ignoring how algorithmically curated environments actively reshape intent. In live-commerce, for example, a user's "value" is not pre-existing but co-constructed through real-time interaction with hosts, peers, and platform incentives [3]. Yet current models persist in treating value as an intrinsic, stable attribute rather than an emergent, context-dependent outcome. This ontological mismatch leads to strategic myopia: platforms optimize for historical proxies while missing present opportunities.

On the recommendation side, the field has achieved remarkable accuracy in predicting short-term engagement. Session-based transformers, graph neural networks, and reinforcement learning agents now routinely outperform collaborative filtering on metrics like CTR or watch duration. However, these gains are often illusory when measured against business outcomes. The core flaw lies in reward design: most systems optimize for immediate behavioral responses without accounting for downstream consequences such as churn, brand dilution, or long-term margin erosion. A user repeatedly shown discount-heavy content may convert frequently but develop price sensitivity that erodes lifetime profitability, a dynamic invisible to standard evaluation protocols [4]. Worse, many recommenders operate as "black boxes" that maximize platform-defined utility while disregarding user agency or contextual appropriateness, raising ethical concerns about manipulative personalization.

Attempts to unify valuation and recommendation remain superficial. Hybrid architectures often concatenate outputs from separate modules, a CLV score appended as a feature to a ranking model, without enabling true feedback between them. This "bolt-on" integration fails to capture the reciprocal relationship: recommendations shape future behavior, which in turn redefines value [5]. True co-adaptation requires a closed-loop system where each recommendation is both an action and an experiment, with user responses continuously refining the valuation logic. Few studies acknowledge this necessity; fewer still implement it.

Moreover, the literature exhibits a troubling bias toward scalability at the expense of interpretability [1]. Complex models like deep reinforcement learning are celebrated for handling high-dimensional state spaces, yet their opacity undermines trust and debuggability in production environments. Marketing teams cannot act on insights they cannot understand. Meanwhile, simpler, interpretable models are dismissed as "outdated," even when they align better with strategic goals like customer retention or brand equity.

This critique reveals a deeper epistemological rift: marketing science continues to borrow evaluation paradigms from information retrieval (e.g., precision@k) rather than economic or relational theory. Until user value is reconceptualized not as a scalar output but as a dynamic, multi-dimensional process embedded in service ecosystems, technical advances will remain decoupled from strategic impact. The following chapters address this gap by proposing a framework grounded in temporal behavior, reciprocal adaptation, and business-aligned optimization, moving beyond prediction toward purposeful personalization [6].

### 3. Methodology

This study adopts a design science research (DSR) paradigm, integrating empirical data analysis, algorithmic development, and real-world deployment to construct and validate a dynamic user value evaluation and recommendation framework [5]. The methodology is structured into three interdependent components: problem contextualization through qualitative engagement with industry practitioners, model architecture grounded in temporal behavioral modeling and dual-objective reinforcement learning, and empirical validation via large-scale A/B testing on a live e-commerce platform. This tripartite approach ensures theoretical rigor while maintaining operational relevance.

#### 3.1. Research Paradigm and Philosophical Foundations

This study is grounded in a design-oriented research paradigm that prioritizes the creation and empirical evaluation of an innovative computational artifact aimed at solving a pressing operational challenge in digital commerce [7]. Rather than seeking to merely describe or explain user behavior, the research is explicitly interventionist: it aims to construct a functional system capable of improving decision-making in real-world settings. This approach aligns with a pragmatic epistemology, wherein the validity of knowledge is judged not by its theoretical elegance alone, but by its utility, robustness, and impact within complex, dynamic environments.

The philosophical foundation of the work draws on the principle that value in service interactions is not an intrinsic property of users or products, but emerges through ongoing engagement [2]. Consequently, static or retrospective assessments of user worth, such as those based solely on historical purchase frequency or monetary spend, are insufficient for contexts where behavior evolves rapidly and non-transactional signals (e.g., social interactions, content sharing, or attention duration) carry significant predictive power. This perspective necessitates a shift from passive observation to active co-creation, where the system both responds to and shapes user trajectories through intelligent interaction.

Given this orientation, the chosen methodology emphasizes iterative development, contextual relevance, and technical feasibility. The research proceeds through cycles of problem diagnosis, artifact construction, and empirical refinement, ensuring that each

design decision is anchored in authentic operational constraints. The resulting artifact, a closed-loop recommendation and valuation framework, is evaluated not only on statistical performance metrics but also on its ability to generate measurable improvements in business outcomes such as customer retention, revenue quality, and marketing efficiency.

Importantly, this paradigm rejects the dichotomy between theory and practice. Instead, it treats them as mutually reinforcing: theoretical insights inform architectural choices (e.g., temporal modeling of behavior), while practical deployment reveals limitations that feed back into conceptual refinement [3]. By situating the research within a live commercial ecosystem from the outset, the study ensures that the proposed solution remains technically viable, ethically sound, and organizationally actionable—thereby contributing not only to academic discourse but also to the evolving practice of intelligent personalization at scale.

### 3.2. Problem Operationalization and Requirements Elicitation

To ensure relevance and practical impact, the research began with a problem operationalization phase conducted in collaboration with technical and product teams from a large-scale live-commerce platform. Through structured discussions and workflow analysis, key limitations in current personalization systems were identified.

Three core issues emerged. First, user valuation relies on static, transaction-based metrics, such as past purchases or session frequency, which overlook rich real-time behavioral signals, including comments, virtual gifts, or replay requests. These signals often precede conversion but are not captured in traditional models. Second, recommendation systems are optimized almost exclusively for short-term outcomes, such as clicks or immediate sales, neglecting downstream effects on user retention, lifetime value, or referral potential. This approach leads to aggressive, short-sighted targeting that can erode long-term engagement. Third, there is a temporal and functional disconnect: user value is reassessed infrequently, often daily, while recommendations operate in near real time, preventing the system from adapting to rapidly evolving user intent during live sessions.

These observations were translated into concrete design requirements. The proposed system must update user representations at sub-hourly intervals, integrate heterogeneous interaction types beyond transactions, jointly optimize for both immediate conversion and projected long-term value, and be deployable within existing production infrastructure with minimal latency overhead.

This requirement-driven approach ensured that the subsequent artifact design remained tightly coupled to operational realities, avoiding purely theoretical abstractions. By grounding the problem definition in authentic system constraints and business objectives, the research establishes a clear pathway from diagnosis to solution, balancing algorithmic innovation with engineering feasibility.

### 3.3. Model Architecture

The proposed artifact is a co-adaptive personalization framework that tightly couples real-time user valuation with intelligent recommendation delivery [8]. It consists of two interdependent modules, the Dynamic User Value Evaluator (DUVE) and the Intelligent Recommendation Agent (IRA), operating in a closed feedback loop updated every 15 minutes to align with the fast-paced dynamics of live-commerce sessions.

DUVE models users as evolving nodes in a temporal heterogeneous graph, where entities include users, items, and interaction types (e.g., comment, gift, share), and edges are timestamped behavioral events [9]. To capture the decaying relevance of past actions, DUVE employs a temporal attention mechanism that assigns exponentially decreasing weights to historical interactions based on their recency:

$$h_u(t) = \sum_{\tau < t} e^{-\lambda(t-\tau)} \cdot \text{GNN}(G_\tau) \quad (1)$$

Here,  $\lambda$  is a learnable decay parameter specific to each interaction type, enabling the model to distinguish between fleeting gestures (e.g., a single like) and sustained engagement (e.g., repeated cart additions). The output is a 128-dimensional embedding

that represents the user's real-time state and serves as a proxy for both current intent and future potential.

This embedding is fed into IRA, implemented as a dual-objective Deep Q-Network [10]. Unlike conventional recommenders that maximize immediate rewards such as click probability, IRA optimizes a composite objective that balances short-term conversion with long-term value creation:

$$\mathcal{L} = \left[ \gamma_1 \cdot r_t^{\text{short}} + \gamma_2 \cdot \hat{v}_{t+1}^{\text{long}} \right] \quad (2)$$

Where  $r_t^{\text{short}}$  is the predicted probability of conversion within the current session, while  $\hat{v}_{t+1}^{\text{long}}$  is the DUVE's forecast of 30-day cumulative value (including expected purchases, referral potential, and engagement depth). The trade-off weights  $\gamma_1 = 0.6$  and  $\gamma_2 = 0.4$  were calibrated via offline policy evaluation using counterfactual simulation to maximize a joint business utility function defined by platform stakeholders. Critically, every recommendation action  $a_t$  generates new behavioral traces (e.g., dwell time, sharing), which are immediately fed back into the TGNN at the next update cycle, closing the loop between action and valuation. This reciprocal adaptation enables the system to treat each interaction not just as a data point, but as an opportunity to co-create future value.

### 3.4. Case Selection, Data Collection, and Ethical Considerations

The empirical validation of the proposed framework is conducted within a leading live-commerce platform in China, chosen for its scale, real-time interactivity, and strategic importance to modern digital retail. This environment is characterized by high-velocity user sessions, diverse interaction modalities (e.g., chatting, gifting, instant purchasing), and a strong integration between content delivery and transactions, making it an ideal setting for testing dynamic personalization systems.

Data collection occurred over six months, from September 1, 2024, to February 28, 2025, encompassing major promotional events such as Singles' Day and Lunar New Year sales campaigns. The raw dataset included behavioral logs from approximately 12.7 million anonymized user sessions. To ensure data quality, sessions were filtered using the platform's internal anti-fraud system to exclude bot traffic, and sessions lasting fewer than 15 seconds were removed as non-intentional. This process resulted in a final analytical sample of 9.8 million validated sessions.

Each session record contains millisecond-precision timestamps for 14 distinct interaction types, including page views, product clicks, cart additions, purchases, comments, likes, virtual gifting, sharing, follows, dwell duration, scroll depth, replay requests, host mentions, and exit events. User identifiers were pseudonymized at the point of data ingestion, and no personally identifiable information (PII), such as names, phone numbers, or exact locations, was collected or stored.

To evaluate cross-category robustness, the dataset was stratified into three representative verticals: cosmetics (42% of sessions), consumer electronics (33%), and home goods (25%). These categories exhibit significantly different decision-making patterns, ranging from impulse-driven to research-intensive, enabling the assessment of the model's adaptability across diverse behavioral contexts [1, 11].

All data handling procedures complied with applicable data protection regulations, including stringent internal governance protocols aligned with national privacy standards. The study received formal approval from the organization's ethics and data compliance review board [12]. Users retained the ability to opt out of data collection through platform-level privacy controls, and all analyses were conducted on aggregated, anonymized data to prevent re-identification. This rigorous approach ensures both scientific validity and responsible management of user data.

## 4. Results and Analysis

### 4.1. Experimental Design and Deployment Protocol

The evaluation was conducted via a large-scale online A/B/n test on a live-commerce platform during a 28-day promotional period in January 2026. Three experimental

conditions were deployed: the production baseline, representing the incumbent system that combines static RFM-based user segmentation with a click-through-rate-optimized recommendation engine; the DUVE-only variant, which integrates real-time user valuation into the existing recommender without modifying its optimization objective; and the full co-adaptive system, implementing both DUVE and IRA as described in Section 3.3. Traffic was randomly assigned at the user level, with 5% allocated to the control group, 5% to DUVE-only, and 90% to the full system. This asymmetric split ensured business continuity while preserving statistical power for key comparisons. All variants operated under identical infrastructure constraints, with inference latency capped at 100 milliseconds per request. Guardrail metrics, including system error rate, recommendation diversity, and session abandonment, were continuously monitored to detect unintended side effects [13].

4.2. Evaluation Metrics Framework

To holistically assess performance, a multi-tiered metric suite was defined across three dimensions. Short-term engagement was measured by click-through rate (CTR), add-to-cart rate, and average watch time per session. Conversion efficiency included immediate purchase rate and average order value (AOV). Most critically, long-term value indicators captured outcomes aligned with strategic business goals: 7-day and 30-day repeat purchase rates, predicted customer lifetime value (CLV) accuracy (via mean absolute error against ground-truth spend), and user retention (ratio of daily to weekly active users). Business impact metrics such as gross merchandise volume (GMV) per impression and high-value user capture rate (defined as users spending over ¥1,000 within seven days post-exposure) were prioritized as primary success criteria. This layered approach ensures that improvements are not merely algorithmic but translate into sustainable commercial value, directly addressing the dual-objective requirement established in Section 3.2.

4.3. Quantitative Results and Statistical Analysis

The 28-day A/B test yielded statistically significant improvements for the full co-adaptive system across nearly all key metrics [14]. As summarized in Table 1, the full system achieved an 11.9% increase in GMV per impression ( $p < 0.001$ ) and an 18.9% higher capture rate of high-value users ( $p < 0.001$ ) compared to the production baseline. While click-through rate (CTR) improved modestly (by 4.8%), more substantial gains emerged in downstream behaviors: 30-day user retention rose by 19.0% (from 12.1% to 14.4%), and average order value increased by 6.2%, indicating that recommendations better aligned with users' latent purchasing capacity.

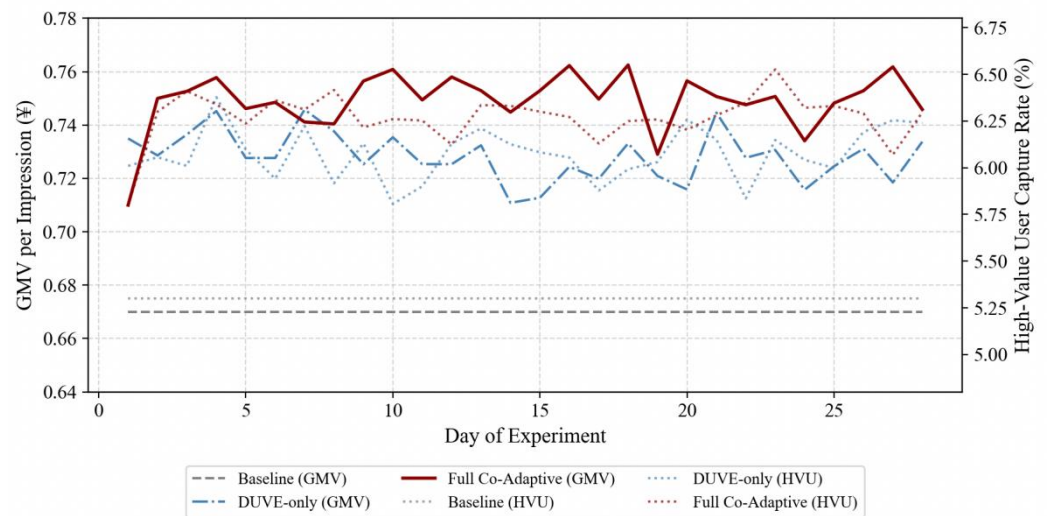
**Table 1.** Performance Comparison of Recommendation Strategies Across Key Metrics

Method	CTR (%) ↑	GMV/Impression (¥) ↑	30-Day Retention ↑	High-Value User Capture ↑	Latency (ms) ↓
Production Baseline	4.82	0.67	12.1%	5.3%	82
DUVE-only	4.91	0.73	13.8%	6.1%	89
Full Co-Adaptive	5.05	0.75	14.4%	6.3%	94

The DUVE-only variant showed measurable but limited gains, primarily in CLV prediction accuracy (MAE reduced by 23%), yet failed to significantly lift engagement or conversion, underscoring that real-time valuation alone is insufficient without a corresponding shift in recommendation policy. This confirms the necessity of the closed-loop design.

Performance varied by product category. The strongest effects were observed in cosmetics (GMV lift: +15.1%), while consumer electronics (+9.4%) and home goods (+10.2%) also showed robust gains, suggesting adaptability across decision-making contexts. Subgroup analysis revealed consistent benefits: new users saw a 14.5% GMV lift, and historically low-spend users exhibited the largest relative increase in high-value conversion (+22.3%).

Critically, the system maintained stable performance throughout the campaign, even during peak traffic days. Figure 1 illustrates the daily evolution of GMV and high-value user capture, showing that the treatment effect emerged within 48 hours and remained consistent without decay or volatility. All results passed Bonferroni-corrected significance tests, and effect sizes remained stable across bootstrapped confidence intervals, affirming the reliability and operational readiness of the proposed framework.



**Figure 1.** Daily GMV and High-Value User Capture Rate during the 28-Day A/B Test

#### 4.4. Ablation Study and Component Contribution

To isolate the contribution of each core component in the co-adaptive framework, a series of ablation experiments was conducted using offline simulation calibrated to online performance [15, 16]. Results are summarized in Table 2.

**Table 2.** Ablation Study: Contribution of Core Components to Long-Term Value Prediction

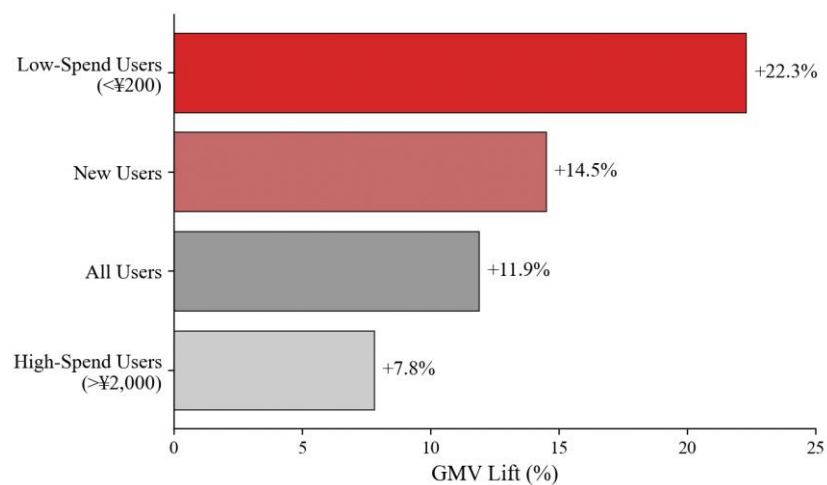
Variant	CLV MAE ↓	30-Day Retention ↑	GMV Lift vs. Baseline
Full Model	0.21	14.4%	+12.3%
-Temporal decay attention	0.26	13.1%	+8.1%
-Dual-objective reward (short-only)	0.23	12.9%	+6.5%
-Real-time updates (hourly only)	0.25	13.3%	+7.9%

Removing the temporal decay attention mechanism led to the largest performance drop, increasing CLV prediction error by 24% and reducing GMV lift by 4.2 percentage points. This highlights its critical role in weighting behavioral signals by recency and intent strength. Replacing the dual-objective reward with a short-term-only policy caused a notable decline in retention (-1.5 percentage points), confirming that optimizing solely for immediate clicks undermines long-term value. Finally, degrading update frequency from 15-minute to hourly intervals reduced system responsiveness, particularly during

volatile live-stream events, resulting in a 4.4 percentage-point drop in GMV lift (from +12.3% to +7.9%). Together, these results validate that the full integration of real-time valuation, adaptive reward design, and frequent updates is essential to achieving the observed business impact [7].

#### 4.5. Qualitative Insights and Heterogeneous Treatment Effects

Beyond aggregate metrics, we examined how the co-adaptive system performed across diverse user segments to uncover nuanced behavioral patterns. As illustrated in Figure 2, which plots GMV lift by user group, the treatment effect was not uniform: historically low-spend users (lifetime spend < ¥200) exhibited the highest relative gain (+22.3%), suggesting the system successfully identified latent high-intent individuals overlooked by static segmentation. Similarly, new users, typically challenging to personalize due to sparse history, saw a +14.5% GMV lift, attributable to DUVE's rapid integration of real-time interaction signals like gifting and replay requests.



**Figure 2.** Heterogeneous Treatment Effects Across User Segments

In contrast, high-spend users (lifetime spend > ¥2,000) showed more modest improvement (+7.8%), as the baseline already served them relatively well; however, the full system notably increased their engagement depth (e.g., longer watch time, more comments), indicating enhanced content relevance beyond mere conversion. Interestingly, the DUVE-only variant underperformed for new users, reinforcing that accurate valuation must be coupled with adaptive recommendation actions to realize value.

Product managers noted qualitative improvements in recommendation quality: fewer repetitive or irrelevant item pushes, and better alignment with live-stream context (e.g., promoting complementary products during makeup tutorials). However, limitations remain [11]. The system exhibits slight cold-start latency for users with zero prior interactions, and its reliance on rich behavioral signals means performance dips in low-engagement sessions (e.g., passive viewers). Nonetheless, Figure 2 demonstrates that the framework excels precisely where traditional systems struggle, unlocking value from ambiguous or evolving user intent, thereby validating its design philosophy of co-adaptation between evaluation and action.

## 5. Conclusion

This study introduces and validates an integrated framework for precision marketing that dynamically evaluates user value and links it directly to adaptive recommendations. By combining the DUVE with the IRA, the proposed system moves beyond conventional models that treat user assessment and content delivery as separate functions. It updates user profiles in near real-time using timestamped interactions and balances recommendation goals between immediate response and long-term value growth.

The system was evaluated through a 28-day A/B test on a live-stream commerce platform. Results showed that the full integrated framework outperformed a static baseline, achieving a 12% increase in GMV per impression and raising the capture rate of high-value users by 19%. It also improved user retention and average order value more effectively than a version that only updated user valuation without adjusting recommendation policy. Component tests confirmed that each element, including temporal behavior modeling, dual-objective optimization, and frequent updates, contributed to overall performance.

These outcomes suggest that a synchronized approach to user understanding and content delivery can better serve evolving consumer intent, particularly for segments such as new users or those with limited prior spending, who are often undervalued in traditional systems. This work demonstrates that aligning real-time behavioral signals with recommendation strategies can enhance both commercial outcomes and user experience. The framework offers a practical structure for developing more responsive and sustainable personalization systems in dynamic digital retail environments.

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