

Original Research Article

Research on characteristics of live e-commerce user consumption behavior and precision marketing strategies based on big data analysis

Hao Sun

Communication University of China Nanjing, Nanjing, Jiangsu, 211172, China

Abstract: Live e-commerce converts shopping into a live, interactive, data-rich decision scene in which product exposure, host credibility, time pressure, peer response, platform recommendation, payment convenience, and after-sales expectation jointly shape consumption behavior. Big data analysis makes these behavioral records useful when click paths, dwell time, coupon response, comment sentiment, purchase intervals, refund causes, and repeat visits are interpreted as connected evidence rather than isolated indicators. The main behavioral characteristics include impulse activation under limited-time offers, trust transfer from streamer to product, comparison avoidance during dense interaction, and loyalty decay when post-purchase service fails to match live-room promises. Precision marketing should therefore move beyond broad traffic purchase and build segmented offers from real-time behavior, value sensitivity, category preference, risk tolerance, service experience, and retention signals. A practical strategy combines clean data capture, feature identification, user segmentation, controlled offer delivery, and feedback update so that conversion, repeat purchase, and consumer protection remain aligned.

Keywords: live e-commerce; user consumption behavior; big data analysis; precision marketing; user segmentation

1. Introduction

Live e-commerce has become a retail format in which consumers evaluate products while watching demonstrations, comments, promotions, and host explanations at the same time. The purchase decision is no longer formed only through search and price comparison; it is shaped by live-room rhythm, social proof, platform ranking, payment convenience, and the perceived scarcity of offers. Big data analysis gives merchants a way to read these behavioral records, but the value of analysis depends on whether the platform can connect behavior before, during, and after the order. A consumer who watches for twelve minutes, asks one specification question, saves a coupon, and abandons payment carries a different marketing meaning from a consumer who clicks directly from a short clip and returns the product two days later. The analysis identifies behavior characteristics specific to live e-commerce and converts them into precision marketing strategies that can be measured, adjusted, and limited by service quality.

2. Big data recognition of live e-commerce consumption behavior

2.1. Streamer-mediated interaction signals shaping purchase intention

Live-room consumption behavior is marked by compressed decision time, dense interaction signals, and a short distance between attention and payment. A user may enter from a recommendation feed, stay through a demonstration, post a question, compare comments, claim a coupon, and complete payment within the same session. The first usable indicator appears before payment: In a platform log with 1000 room entrants and 420 product-card clicks, the click rate is 420 out of 1000, or 42.0%, which separates active inspection from ordinary exposure^[1]. Intention often rises after a visible answer from the host or after peer comments reduce perceived risk. Trust transfer can be measured in the same interaction stream: In a room with 300 product questions, 90 questions about authenticity or warranty produce a risk-question

share of 90 out of 300, or 30.0%. Such a level should push the merchant to adjust proof materials, platform badges, and service scripts before increasing traffic spending, because unresolved trust friction later raises refund review, complaint handling, customer-service workload, and the cost of rebuilding credibility in the next broadcast.

2.2. Retention segmentation from value-sensitive behavior signals

Segmentation in live e-commerce should start from behavior that changes marketing action. Value-sensitive users respond to price anchors, coupons, and bundle rules, while category-loyal users return for a product line even when the discount is moderate. New visitors need credibility and product explanation; repeat buyers need stock stability, after-sales clarity, and member benefits. A useful segment is built from at least four groups of variables: Session depth, promotion response, category history, and post-purchase retention^[2]. In a monthly cohort with 260 repeat buyers and 156 second purchases, the repeat-purchase rate is 156 out of 260, or 60.0%. If the same cohort produces high return requests after one category, the segment should not be labeled simply as loyal.

3. Precision marketing strategy design under big data analysis

3.1. Risk-controlled matching for impulse purchase offers

Impulse consumption is common in live rooms, but precision marketing should not confuse momentary excitement with stable demand. Limited-time countdowns, inventory prompts, gifts, and comment pressure can accelerate payment when a user has already shown category interest; the same tactics can create regret, return costs, and negative reviews when the product does not fit. Offer matching should use risk scores that include price jump, abnormal order frequency, repeated refund history, and mismatch between viewed category and purchased item^[3]. In a controlled campaign design, users with at least 8 minutes of viewing time, 2 product-card clicks, and 1 specification question receive comparison content before a coupon, while users with less than 60 seconds of viewing receive product education rather than a hard discount. This rule limits waste because the offer is tied to observable readiness and reserves stronger incentives for consumers whose behavior shows category fit, enough information intake, and a lower probability of returning the product after delivery. It also protects the merchant from paying for conversions that are likely to return as refunds, low ratings, or service disputes.

3.2. Feedback-controlled behavior-to-offer marketing process

A practical precision marketing strategy needs a controlled process that begins with clean data capture and ends with feedback update. The platform should capture room entry source, viewing duration, comment topic, product-card click, coupon action, payment result, logistics status, return reason, and repeat visit interval under one user identity rule. Feature identification separates high-intention users from curiosity traffic and service-risk users^[4]. A weekly process can set 24 hours as the maximum delay for payment and refund synchronization, use 7 days as the repeat-visit observation window, and trigger tag review when one segment records refund claims above 15 orders per 100 paid orders. Segmentation converts those features into marketing groups, while offer delivery selects product bundles, coupons, explanation scripts, and follow-up messages within a 2-contact weekly frequency limit. **Figure 1** presents the sequential process that turns behavior data into precision offer delivery and sends retention evidence back to the next live-room cycle.

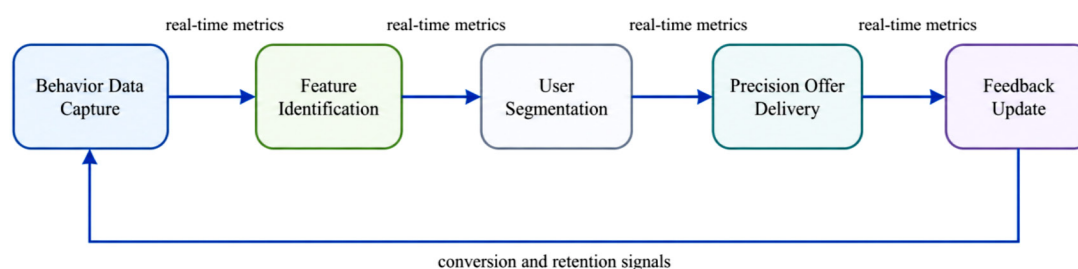


Figure 1. Feedback-controlled behavior-to-offer process for live e-commerce precision marketing.

3.3. Data governance rules for marketing adjustment

Precision marketing remains reliable only when data governance is built into the marketing cycle. Live-room data can contain duplicate identities, device sharing, misleading traffic, delayed refund records, and comment noise, so the merchant should define cleaning rules before building user tags. One campaign comparison can use 1600 exposed users as the denominator: 80 paid orders create a baseline conversion rate of 80 out of 1600, or 5.0%, and 112 paid orders after offer adjustment create a revised rate of 112 out of 1600, or 7.0%. The 32-order increase equals 2.0 percentage points, but the same evaluation must include service risk^[5]. If refunds rise from 8 to 24 orders, the refund count triples and the apparent gain becomes unstable. Governance should also require deletion of expired tags after 30 days without a relevant visit, because stale labels can keep pushing the wrong category after consumer preference changes across season, income pressure, product availability, or competing platform exposure. A sustainable plan uses weekly model review, monthly tag pruning, and campaign-level service audits so that marketing improves transaction efficiency without hiding fulfillment pressure or dissatisfaction. The review should also compare high-value segments with ordinary visitors, because a higher order value is not useful when the same group produces slower complaint closure or repeated product mismatch.

4. Conclusion

Live e-commerce user consumption behavior and precision marketing based on big data analysis should be understood as one connected decision system. Users show compressed purchase paths, trust transfer from streamer to product, price-sensitive impulse response, and retention patterns that appear only when live-room interaction is joined with fulfillment and after-sales records. Big data analysis supports precision marketing by turning these records into usable features, but the strategy fails when traffic, coupons, and conversion are optimized without service-risk control. The more workable approach is to capture behavior data continuously, identify meaningful features, segment users by action relevance, deliver offers within frequency and risk limits, and update the next campaign with conversion, refund, complaint, and repeat-purchase signals. Under this structure, precision marketing is not a stronger push toward every viewer; it is a disciplined match between consumer readiness, product suitability, platform credibility, relationship value, and the service capacity that keeps live-room promises credible after payment.

References

- [1] Yang D ,Zhu Y ,Liu S .Focusing on Characteristic Industries: Research on the Optimization of the Value Chain of Hainan's Tropical High-Efficiency Agriculture Driven by Big Data[J].Innovation Series: Advanced Science,2025,2(6).
- [2] Hu Z .Research on Big Data Analysis of Martial Arts Culture and Cultural Inheritance Strategies from the Perspective of Digital Humanities Theory[J].Journal of Modern Education and Culture,2025,2(6).
- [3] Wang B ,Ding C ,Sun H , et al. Research on the Energy Consumption Distribution Characteristics of Long-Distance Pipelines Based on Big Data Models[J].Chemistry and Technology of Fuels and Oils,2026,(prepublish):1-13.
- [4] Lehan W ,Xin Z .Research on urban vitality space characteristics and influence mechanism based on multiple big data: a case of Wuhan central urban area[J].Environmental Research Communications,2026,8(7):075008-075008.
- [5] Jing W .Three Core Characteristics of Big Data Analysis and Their Significance[J].Scientific and Social Research,2026,8(4):151-158.