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Application Analysis of User Behavior Segmentation in Enhancing Customer Lifetime Value

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Abstract

User behavior segmentation is a crucial method for understanding and managing customer heterogeneity, enabling enterprises to adopt a data-driven approach to customer classification. This study, based on user behavior data, investigates the role of behavior segmentation in enhancing customer lifetime value (CLV). By systematically collecting and organizing data, calculating key indicators, and estimating lifetime value, enterprises can identify high-value customer segments and develop targeted management strategies. The application of behavior-based segmentation enables optimized marketing resource allocation, improved customer loyalty and repurchase rates, and overall enhancement of CLV. This research offers both theoretical support and practical guidance for enterprises to achieve data-driven customer management and precision marketing.

Keywords

User behavior; Lifecycle; Value management; Precision marketing

In an increasingly competitive market environment, enterprises face the dual challenge of rising customer acquisition costs and higher churn rates. How to scientifically identify high-value customers and enhance their long-term contribution has become central to sustainable development. By systematically improving customer lifetime value, enterprises can not only optimize marketing resource allocation and increase return on investment but also strengthen customer loyalty and repurchase behavior, thus ensuring a stable revenue stream. Studying the relationship between user behavior and customer value helps enterprises formulate more precise management strategies in a data-driven decision-making environment, fostering continuous growth amid digital transformation and market competition.

1. Theoretical Foundation of User Behavior Segmentation

User behavior segmentation is a theoretical framework that classifies customers systematically based on behavioral characteristics, focusing on identifying distinct behavioral patterns and potential value among different customer groups. By analyzing multidimensional data such as purchase frequency, spending amount, preference selection, and interaction behaviors, segmentation reveals intergroup differences and provides theoretical support for understanding customer needs and behavioral patterns. The theory emphasizes heterogeneity among customer groups and the quantifiability of individual behaviors, suggesting that customer value depends not only on transaction volume but also on behavioral patterns, loyalty, and long-term contributions. With advances in data analysis theories, behavior segmentation has evolved into a data-driven framework that integrates statistics and behavioral science, forming a robust theoretical foundation for customer relationship management and value assessment.

Behavior segmentation theory also encompasses the academic basis of group identification and potential value

discovery. Research indicates that systematic analysis of behavioral features enables the construction of multi-tiered customer classification structures, helping to identify high-value, potential, and at-risk customers. This theoretical approach supports strategic planning and marketing decisions by interpreting behavioral patterns and customer responses to products and services. Group segmentation not only aids in understanding behavioral regularities but also explains how different customer types contribute differently to enterprise outcomes. By emphasizing data analytics, behavioral pattern recognition, and potential value assessment, this theory has become a crucial component of modern customer management and precision marketing research.

2. Theories and Measurement Methods of Customer Lifetime Value

2.1 Concept and Importance of Customer Lifetime Value

Customer lifetime value (CLV) represents the total value a customer contributes to an enterprise throughout the entire relationship cycle, serving as a vital metric for evaluating long-term contributions and strategic decision-making. Theoretically, CLV reflects not only a customer's spending capacity but also their loyalty, referral potential, and depth of engagement with the enterprise. Understanding CLV enables businesses to identify high-value customer segments, allocate marketing resources efficiently, and design long-term relationship management strategies to promote sustainable development. In theoretical research, CLV is viewed as the bridge connecting customer behavior with enterprise economic outcomes, revealing the temporal dynamics of customer contributions and their value potential. This provides a scientific foundation for precision marketing and customer management.

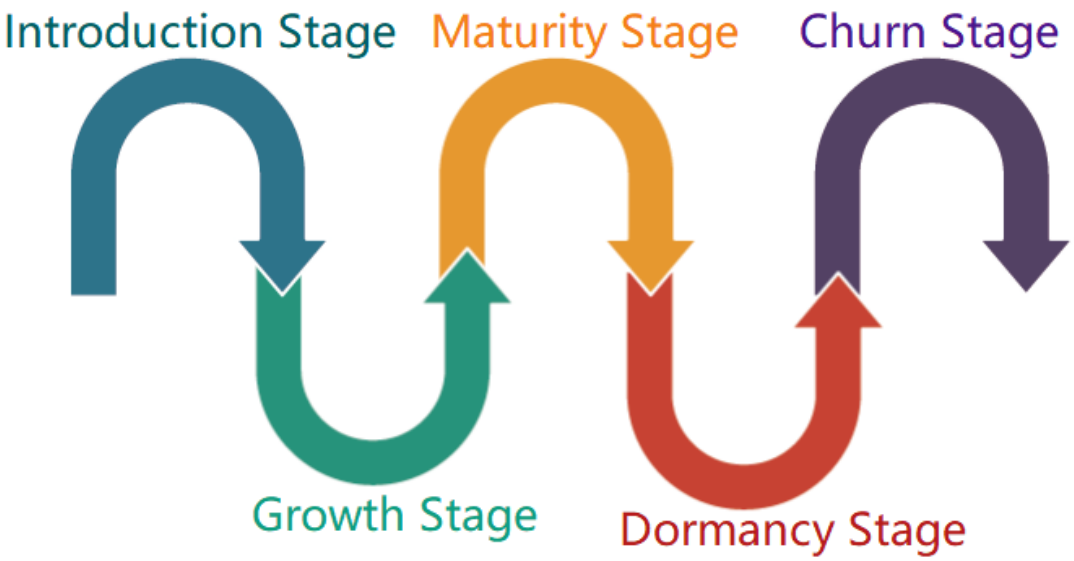

Figure 1. Customer Lifecycle Flowchart.

2.2 Measurement Methods of Customer Lifetime Value

2.2.1 Customer Data Collection and Organization

The foundation for measuring customer lifetime value (CLV) lies in systematically collecting multidimensional data, including customer transaction records, purchase frequency, spending amounts, and interaction behaviors, followed by data cleaning, integration, and structuring to ensure analytical accuracy and operational feasibility. Data collection encompasses not only online transaction information but also behavioral traces across social media, mobile platforms, and offline channels. By establishing a unified data management platform, enterprises can achieve multi-source data integration and real-time updates, providing reliable support for subsequent indicator calculation and model construction (Bae & Yun, 2024). The data cleaning process involves removing outliers, duplicates, and invalid entries while transforming scattered information into quantifiable analytical dimensions. The content and structure of customer data collection and organization are shown in Table 1. Only when data quality is ensured can the CLV measurement results be scientifically valid and practically meaningful, providing a solid foundation for enterprise decision-making.

Table 1. Customer Data Collection and Organization Content

Data Type	Key Indicators	Data Sources	Application Direction
Transaction Data	Purchase frequency, order amount, and average spending per customer	E-commerce system, CRM system	Customer value calculation
Behavioral Data	Browsing duration, click-through rate, and number of interactions	Website logs, app behavior records	Behavioral pattern analysis
Social Data	Number of comments, share rate, brand mentions	Social media platforms	User sentiment analysis
Customer Information	Age, region, occupation, registration time	Registration database	Basis for customer segmentation
Service Data	Complaint records, satisfaction ratings, and customer service interactions	Customer service system	Customer experience improvement

2.2.2 Key Indicator Calculation and Analysis

With the support of foundational data, core indicators for each customer are calculated, including average purchase value, purchase frequency, customer retention rate, and churn probability, providing a basis for quantifying lifetime value and revealing customer behavior patterns and value potential. The selection of core indicators should align with the enterprise's business objectives, as different market environments and customer types may lead to variations in indicator weighting. Through data modeling and statistical analysis, enterprises can identify patterns of customer value distribution across the consumption cycle and assess future contribution trends. In practice, these indicators not only provide theoretical support for CLV measurement but also help monitor changes in customer structure, identify high-risk groups, and adjust marketing strategies promptly, achieving dynamic customer management and maximizing long-term value.

Common formulas for calculating key indicators are as follows:

$$ARPU = \frac{Total\ Customer\ Expenditure}{Number\ of\ Purchases}$$

$$Retention\ Rate = \frac{Number\ of\ Customers\ at\ the\ End\ of\ the\ Period - Number\ of\ New\ Customers}{Number\ of\ Customers\ at\ the\ Beginning\ of\ the\ Period}$$

In the formula, $ARPU$ represents the average purchase value per customer, used to measure an individual customer's spending capacity; total customer spending refers to the aggregate transaction amount of all customers within the study period; purchase frequency indicates the number of transactions made by a customer during the same period; customer retention rate reflects the proportion of customers retained over a certain period; the end-period customer count denotes the number of customers still active at the end of the period; the number of new customers during the period represents the total newly acquired users; and the beginning-period customer count refers to the number of customers at the start of the analysis period (Farid, Negar, & Yasser, 2024).

2.2.3 Customer Lifetime Value Calculation and Forecasting

Based on the key indicators, customer lifetime value (CLV) is calculated and forecasted using historical data methods, predictive models, and probabilistic models, enabling dynamic evaluation of a customer's potential contribution in future periods. This provides enterprises with a scientific framework for customer value management and supports long-term strategic decision-making. Traditional historical data methods are suitable for stable customer relationships, while in highly competitive and rapidly changing markets, predictive and probabilistic models better capture the dynamic characteristics of customer behavior. By establishing CLV prediction models based on time series analysis, regression, or machine learning algorithms, enterprises can achieve precise and real-time forecasting of customer value. This approach not only enhances analytical accuracy but also guides marketing budget allocation and customer relationship management, ensuring sustained competitive advantage and long-term revenue growth.

The classic formula for calculating customer lifetime value is:

$$CLV = \sum_{t=k}^{T} \frac{R_t - C_t}{(1+d)^t}$$

In the formula, CLV represents the customer lifetime value, is the net profit generated by the customer over the entire relationship period; R_t denotes the revenue contributed by the customer in period t; C_t is the cost of maintaining the customer in period t; d represents the discount rate, reflecting the time value of money; and T indicates the duration of the customer relationship or the forecast time horizon. This model comprehensively considers revenue, costs, and discounting factors, allowing dynamic reflection of a customer's net contribution over different time periods (Li, Zhu, & Li, 2025). It provides enterprises with a scientific basis for customer segmentation management and supports quantitative analysis for marketing strategy optimization and investment decision-making.

3. Application of User Behavior Segmentation in Enhancing Customer Lifetime Value

3.1 Identification and Analysis of Different Behavior Groups

The process of identifying and analyzing user behavior groups primarily involves four steps: data collection, feature selection, model construction, and result interpretation. Enterprises need to establish a robust data infrastructure to systematically collect multidimensional data on customer purchase frequency, transaction amounts, interaction behaviors, and channel preferences, and perform standardization and cleaning to ensure analytical accuracy and comparability. During the feature selection stage, core variables reflecting customer differences, such as consumption cycle, purchase activity, product preferences, and depth of service interaction, are identified through correlation analysis and importance evaluation. Based on these features, clustering analysis, principal component analysis, or K-means algorithms are used to construct segmentation models for scientific classification of customers (Chen & Zhou, 2025). Finally, through model validation and visualization, the behavioral characteristics, spending potential, and lifecycle stages of each group are interpreted, creating a closed-loop system from data collection to behavioral insight and providing reliable decision-making support for precision marketing and resource allocation. This identification process reflects the integration of data analytics and behavioral science, enabling enterprises to dynamically understand customer differences and continuously optimize management strategies (Zhang, 2025).

In practice, a European e-commerce company applied this process to establish a customer behavior segmentation system. The company integrated online transaction data, social media interaction records, and app usage behavior, and selected variables such as purchase cycle, interaction frequency, and preferred product categories. Using machine learning clustering algorithms, customers were divided into high-value, potential, and low-activity groups. Targeted strategies were developed for each segment: high-value customers received exclusive membership services and after-sales support, potential customers were nurtured through promotional campaigns and content recommendations, and low-activity customers were re-engaged via remarketing and personalized alerts. This process enabled dynamic optimization of the customer structure, improved targeting and efficiency of marketing resources, and established a behavior-driven customer value growth system.

3.2 Design and Implementation of Personalized Marketing Strategies

The design and implementation of personalized marketing strategies typically involve four stages: customer insight, strategy design, content matching, and effect evaluation. Enterprises first leverage behavior segmentation to identify differences in customer needs and preferences, creating detailed customer profiles. Based on these profiles, differentiated marketing strategies are developed, including product recommendations, pricing methods, and promotional schedules. Personalized content is then matched to customer characteristics and delivered through automated marketing systems, such as email campaigns, app notifications, or social media channels (Zhang, Huang, & Peng, 2025). Finally, real-time monitoring of customer responses allows evaluation of marketing effectiveness and iterative strategy adjustments. This workflow creates a dynamic closed loop from insight to execution, enabling continuous optimization and self-learning in personalized marketing.

In practice, a North American online service enterprise successfully applied this process. Based on user habits and purchase preferences, the company established a behavior segmentation model. High-activity users received automated recommendations for product trials and exclusive offers, potential customers were targeted with educational content to increase product familiarity, and low-activity groups were encouraged to return through time-limited

promotions and personalized reminders. By continuously optimizing content and delivery schedules, the enterprise achieved simultaneous improvements in customer engagement and marketing ROI, demonstrating the feasibility of the process and the practical value of behavior segmentation theory.

3.3 Strategies to Enhance User Loyalty and Repurchase Rate

Strategies for improving user loyalty and repurchase rates primarily include three aspects: customer tiered management, incentive mechanism design, and relationship maintenance optimization. Enterprises establish a scientific tiered management system based on behavior segmentation, categorizing customers into core, growth, and general tiers and implementing differentiated maintenance and communication strategies for each. By dynamically monitoring customer behavior and lifecycle stages, enterprises can assess engagement levels and churn risk, enabling targeted interventions. Concurrently, incentive systems incorporating point rewards, membership programs, exclusive activities, and personalized care strengthen emotional connections with the brand and foster continuous interaction. Intelligent feedback systems further monitor satisfaction and behavioral changes, allowing dynamic adjustment of incentive content and frequency, thus achieving refined, adaptive, and long-term loyalty management and creating a data-driven mechanism to retain customers and promote repurchases (Maghsoudi et al., 2025).

In practice, a European retail chain implemented a multi-tiered membership system based on behavior segmentation analysis. High-value customers received exclusive experiences, membership clubs, and personalized consulting; growth customers were offered points accumulation and tiered rewards; general customers received seasonal promotions and vouchers. Regular data analysis monitored repurchase rates, activity participation, and satisfaction, enabling continuous optimization of member benefits and communication strategies to match evolving customer needs. This tiered and data-driven loyalty management system enhanced brand attachment and trust, significantly increasing repurchase frequency and customer lifetime value, enabling the enterprise to maintain stable long-term relationships and revenue growth in a competitive market.

3.4 Marketing Resource Optimization and ROI Enhancement in Practice

Strategies for optimizing marketing resources and enhancing ROI focus on resource allocation, channel optimization, and performance evaluation. Enterprises establish a value-oriented budget allocation system based on customer behavior segmentation and CLV, concentrating resources on high-value and potential customer segments while reducing investment in low-return customers. Additionally, in-depth analysis of channel data is conducted to optimize marketing paths and contact frequency, ensuring precise and efficient resource deployment (Zhao, Ma, & Cao, 2025). ROI monitoring and feedback models evaluate the effectiveness and cost-benefit of marketing activities across segments, forming a sustainable optimization loop. This data-driven approach combines quantitative analysis with dynamic adjustments, maximizing customer value while improving investment returns and supporting long-term growth.

In practice, a technology service enterprise applied this strategy to optimize marketing resource management. Behavior segmentation and CLV analysis identified mid-value customers with high growth potential, leading to budget reallocation from low-conversion channels to high-potential segments. Advertising content and service touchpoints were refined, and ROI was tracked in real-time to dynamically adjust marketing strategy and budget allocation. Through continuous execution, the enterprise significantly improved resource efficiency and ROI while maintaining cost control, demonstrating the practical value and strategic significance of behavior segmentation theory in marketing management.

4. Conclusion

User behavior segmentation effectively enhances customer lifetime value. With the continued development of artificial intelligence and big data technologies, enterprises' capabilities in data analysis for customer value management will further improve, and behavior segmentation models will become more intelligent and dynamic. By introducing real-time data monitoring and predictive analytics, enterprises can make accurate judgments and strategy adjustments at early stages of customer behavior changes, achieving higher-level customer relationship management and value growth. Data security and privacy protection will become key areas of future research and application. Enterprises that deepen intelligent analysis while ensuring compliance will maintain long-term competitive advantage and sustainable development momentum.

References

Bae, J., & Yun, H. M. (2024). Driving change to electric vehicles: A comprehensive study of electric vehicle user segmentation and charging behaviors. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *68*(1), 928-934.

Chen, X., & Zhou, Y. (2025). User behavior on value co-creation in human–computer interaction: A meta-analysis and research synthesis. *Electronics*, *14*(6), 1071.

Farid, H., Negar, M., & Yasser, Z. (2024). From user behavior to subscription sales: An insight into e-book platform leveraging customer segmentation and A/B testing. *Services Marketing Quarterly*, *45*(2), 153-181.

Li, P., Zhu, X., Li, X., et al. (2025). Research on mitigating popularity bias in federal recommendation based on users' behavior. *The Journal of Supercomputing*, *81*(4), 616.

Maghsoudi, M., Khosravi, J. M., Valikhani, H. M., et al. (2025). Identifying and analyzing movie websites ecosystem based on user behavior: A social network analysis perspective. *SN Computer Science*, *6*(2), 168.

Zhang, H., Huang, H., & Peng, C. (2025). A novel user behavior modeling scheme for edge devices with dynamic privacy budget allocation. *Electronics*, *14*(5), 954.

Zhang, Z. (2025). Research on interaction experience oriented environmental design of public space—Dynamic response design based on AR technology and user behavior. *World Science Review*, *2*(3), 38-40.

Zhao, S., Ma, C., & Cao, Z. (2025). Improved multi-objective strategy diversity chaotic particle swarm optimization of ordered charging strategy for electric vehicles considering user behavior. *Energies*, *18*(3), 690.