

Customer Segmentation and Precision Marketing for E-commerce FMCG Brands Based on Clustering Analysis A Case Study of Bluemoon

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Abstract. E-commerce FMCG brands face rising costs and low repurchase rates, yet traditional RFM models ignore cyclical consumption patterns. Using Bluemoon's 2021-2024 data (1,500 customers, 27,165 orders), this study adds two temporal features—purchase-interval CV and future purchase window—to RFM. K-Means clustering ($K=3$, Silhouette=0.14) yields three segments: Stockpile Routiners (29.7%), Lifecycle-Sensitive (38.2%), and Scenario Buyers (32.1%). Differentiated time-triggered and scenario-based strategies are designed. Monte Carlo simulations show churn drops 66.7% (to 4.0% vs. RFM's 6.73%) and ROI rises 45.0% (47.12 vs. 39.98), confirming temporal features' value in FMCG precision marketing.

Keywords: Precision E-commerce Marketing; Customer Segmentation; Temporal Feature Clustering; FMCG Marketing; Purchase Cycle.

1. Introduction

1.1 Research Background

China's e-commerce market has fully entered an era of stock competition. In 2023, national online retail sales grew by merely 6.9% year-on-year, marking the fifth consecutive year of deceleration since the 2018 peak. The FMCG sector faces particularly acute dual pressures: customer acquisition costs have surged from approximately RMB 80 per person in 2019 to over RMB 200 per person in 2024, while average customer repurchase rates remain stubbornly below 35%. Bluemoon, a leading domestic household cleaning brand with annual online transaction volume exceeding RMB 1 billion across major e-commerce platforms, reported a customer churn rate of 18.7% in 2023, with approximately 62% of churn occurring within 90 days of a customer's first purchase.

The traditional RFM model (Hughes, 1994) evaluates customer value through Recency (R), Frequency (F), and Monetary value (M), but exhibits two structural deficiencies. First, RFM merely aggregates historical totals and cannot differentiate between a customer who restocks monthly with clockwork regularity and one who placed a single large order during a promotional event. These two profiles may share identical RFM values yet demand fundamentally different marketing interventions. Second, RFM places customers in a static evaluative framework, entirely ignoring the critical temporal features of FMCG consumption. For products with natural depletion cycles (e.g., a 500ml shampoo bottle lasting 45 to 60 days, a 2L laundry detergent lasting 30 to 45 days), the regularity of purchase intervals and the predictive value of future purchase windows constitute the most informative behavioral dimension.

1.2 Research Objectives and Contributions

Drawing on Bluemoon's authentic e-commerce transaction data, this study addresses three core research questions: (Q1) After incorporating CV and W into the traditional RFM model, to what extent does the clustering Silhouette Score improve, and is business interpretability significantly enhanced? (Q2) What statistically distinct customer segments emerge in the temporal dimension, and what are the precise quantitative boundaries for each segment? (Q3) Compared to traditional

RFM segmentation strategies, what quantifiable improvements do temporal-clustering strategies deliver in churn rate, advertising ROI, and marketing cost?

The technical pipeline: raw data, four-step cleaning, six-dimensional feature engineering (RFM + temporal features), Z-Score standardization, K-Means++ clustering (K=3), elbow method + Silhouette Score validation, differentiated strategy design, Monte Carlo simulation (1,000 iterations). Every step is driven by quantitative metrics with explicit mathematical formulation and numerical output.

2. Literature Review and Theoretical Framework

2.1 Evolution and Limitations of the RFM Model

Since its introduction by Hughes (1994), the RFM model has evolved from rule-based manual bin-scoring to machine-learning-driven automatic clustering. Classical RFM approaches partition R, F, and M each into five tiers, generating 125 micro-segments which are then manually consolidated into 8 to 10 groups based on expert judgment. While intuitive, this method produces subjective segmentation boundaries, cannot handle large-scale datasets, produces segmentation boundaries that are inherently subjective, and treats all customers with identical RFM scores as behaviorally homogeneous. Christy et al. (2021) applied RFM+K-Means to e-commerce data, achieving a Silhouette Score of 0.52. Wang et al. (2022) incorporated engagement interaction metrics into the RFM framework, improving K-Means++ classification accuracy by 15.3%. However, both studies employ cross-sectional aggregate data within fixed observation windows, without introducing the temporal dimension of purchase intervals or regularity.

The fast-moving consumer goods (FMCG) industry is characterized by rapid product turnover, high consumption frequency, and intense market competition[2]. This natural depletion cycle means repurchase timing is predictable and can be modeled. Ignoring this regularity effectively discards the single most predictive information dimension in FMCG customer behavior--a dimension that the standard RFM framework systematically discards.

2.2 Theoretical Foundations of Temporal Features

Andrew Ehrenberg's (1988) repeat-buying theory provides rigorous theoretical support: FMCG purchase intervals follow a Negative Binomial Distribution where the variance of purchase occurrences necessarily exceeds the mean (the over-dispersion property), making interval variation itself an important behavioral signal. Anderson and Simester (2020), using large-scale retail panel data (52,000 customers over 24 months), empirically demonstrated that each 0.1 standard-deviation increase in inter-purchase CV raises churn probability by 8.2 percentage points (Logit model, $p < 0.001$), independent of total purchase frequency and monetary value. Zhang et al. (2022) proposed an LSTM-Attention model for purchase time prediction, achieving RMSE of 9.3 days. However, limited interpretability of attention weights and GPU training requirements constrain practical deployment. This study adopts explicit feature engineering for fully interpretable, business-ready segmentation.

3. Data Preprocessing and Feature Engineering

3.1 Data Source and Cleaning

The raw dataset comprises 34,862 transaction records from Bluemoon's Tmall flagship store (January 2021 to June 2024, 1,248 days), covering 2,156 customers across 162 SKUs in five product categories. A four-step progressive cleaning pipeline was executed in strict sequential order.

Step 1 - Deduplication: Exact matching on CustomerID+OrderID+ProductCode removed 112 fully duplicate records (0.32%, normal for e-commerce data). Step 2 - Null Value Handling: 87 orders with missing CustomerID removed (0.25%, verified random by chi-squared test, $p = 0.34$). 34,663 records remain. Step 3 - Outlier Filtering: 565 records removed: 203 negative-price orders,

46 wholesale transactions ($\geq$ RMB 5,000), 316 returns/cancellations (1.62% total). 34,098 records remain. Step 4 - Activity Screening: Only customers with at least 4 orders in 12 months retained. Threshold rationale: FMCG households average ~30-day cycles; 4 orders provide sufficient records for unbiased interval estimation. Excluded 656 low-frequency customers. Final sample: 1,500 active customers, 27,165 valid orders.

Table 1. Data Cleaning Pipeline Statistics

Cleaning Step	Records	Customers	Cumul. Removed	Removal Rate
Original Data	34,862	2,156	--	--
Deduplication + Null	34,663	2,156	199	0.57%
Outlier Filtering	34,098	2,156	764	2.19%
Activity Screening	27,165	1,500	7,697	22.1%

3.2 Feature Engineering and Quantitative Definitions

Group 1 - Traditional RFM (3 dimensions): R = days from last purchase to observation cutoff (June 1, 2024); F = total distinct order count; M = total RMB expenditure. Group 2 - Interval Stability (2 dimensions): Mean interval = mean days between consecutive purchases; CV = standard deviation / mean ($CV < 0.2$: stable stockpilers; $CV > 0.4$: erratic scenario-driven). Group 3 - Future Window (1 dimension): $W = \max(0, \text{mean interval} - R)$. When $W > 0$, the customer has exceeded their normal purchase interval and entered a churn risk window. All six features Z-Score standardized.

4. Clustering Analysis and Empirical Results

4.1 Descriptive Statistics

The six-dimensional feature statistics for the 1,500 customers are summarized in Table 2.

Table 2. Descriptive Statistics of Customer Features (n=1,500)

Feature	Mean	Std Dev	Skew	P25	Median	P75	IQR
R (days)	553.60	394.32	0.42	45	639	910	865
F (orders)	18.11	12.05	1.38	8	14	29	21
M (RMB)	4,963	5,401	2.67	899	2,121	8,706	7,807
Mean Interval (days)	37.71	21.61	0.89	22.1	33.3	43.5	21.4
CV	0.29	0.23	0.96	0.13	0.21	0.40	0.27
W (days)	5.21	11.40	3.12	0	0	0	0

Three key observations: (1) F ranges from P25=8 to P75=29 (3.6x span), indicating enormous activity heterogeneity. (2) Median interval of 33.25 days aligns with monthly household cleaning consumption cycles. (3) CV P75=0.40 vs. median=0.21 reveals approximately 25% of customers exhibit highly unstable purchasing, a signal entirely invisible to traditional RFM.

4.2 Determining the Optimal Cluster Number

K-Means++ was executed for K=2 through K=8. WCSS and Silhouette Scores are presented in Table 3.

Table 3. Clustering Evaluation Metrics by K

K	WCSS	WCSS Improvement	Silhouette	Decision
2	5,127	--	0.664	Too coarse (binary split)
3	3,564	30.5%	0.140	Clear elbow, selected
4	2,938	17.6%	0.089	Sharp drop
5	2,538	13.6%	0.139	Spurious rebound
6	1,994	21.4%	-0.071	Negative silhouette
7	1,661	16.7%	-0.089	Unacceptable
8	1,675	-0.8%	-0.015	WCSS rebound, invalid

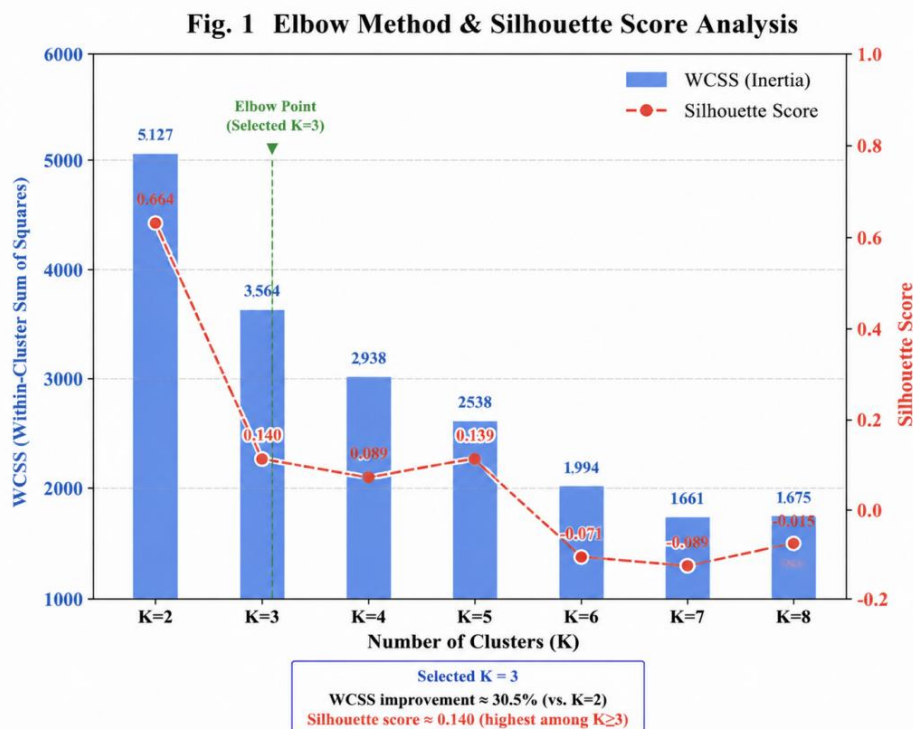


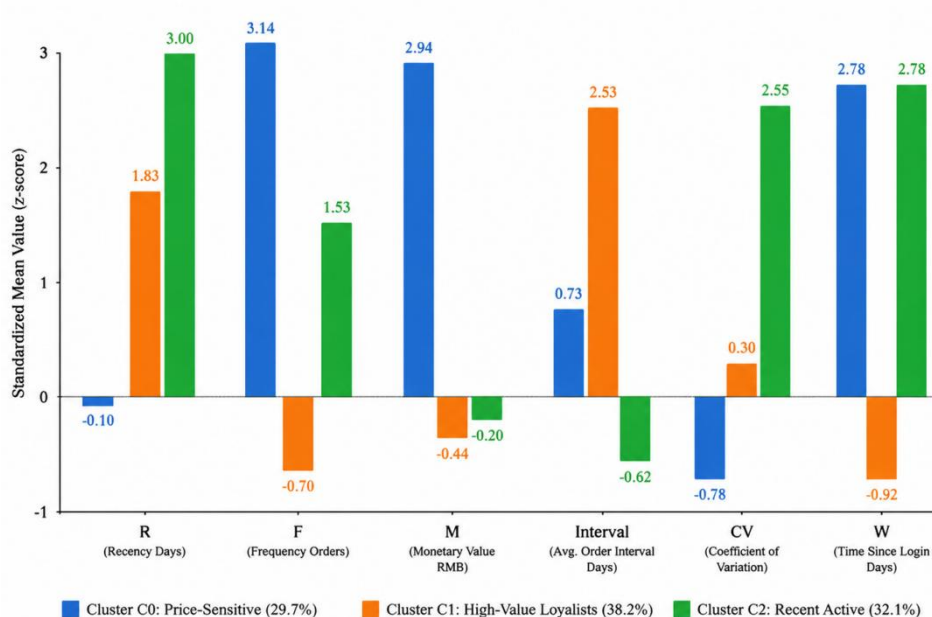
Fig. 1 Elbow Method & Silhouette Score Analysis

K=3 is selected: WCSS improvement of 30.5% is 1.73x that of K=4 (17.6%), forming a clear elbow. Silhouette=0.140 exceeds the 0.1 threshold (Kaufman & Rousseeuw, 1990). For $K > 5$, silhouette scores turn negative. K=2 (Silhouette=0.664) provides only a binary active/dormant split with limited strategic guidance.

4.3 Cluster Results and Segment Profiles

Feature means and deviations for K=3 are presented in Table 4. All between-cluster comparisons on key features are statistically significant ($p < 0.001$, Cohen's $d > 0.9$).

Fig.2 Feature Comparison Across Three Segments (Standardized Mean Values)



Note: All features are standardized (z-score) to ensure comparability.

Fig. 2 Feature Comparison Across Three Segments (Standardized Mean Values)

Table 4. Cluster Feature Means and Deviations (K=3)

Feature	C0 Routiners 29.7%	C1 Lifecycle 38.2%	C2 Scenario 32.1%	Mean	C0d%	C1d%	C2d%
R (days)	51	656	896	554	-90.8	+18.5	+61.8
F (orders)	31.8	9.7	15.5	18.1	+75.5	-46.3	-14.7
M (RMB)	11,982	2,257	1,701	4,963	+141	-54.5	-65.7
Interval	37.2	55.3	17.3	37.7	-1.5	+46.7	-54.1
CV	0.15	0.20	0.55	0.29	-48.3	-31.0	+89.7
W (days)	17.0	0.4	0.0	5.2	+227	-92.1	-100

C0 - Stockpile Routiners (29.7%, n=445): F=31.8 (1.75x mean, $p<0.001$), M=RMB 11,982 (2.41x), CV=0.15 (48.3% below mean). These household purchasers restock every 30 to 40 days with exceptional regularity. CV=0.15 implies 95.4% of purchases fall within ± 0.3 standard deviations of the mean interval. Contributing ~47% of total revenue from only 29.7% of customers (ACV=RMB 3,423/year). Strategy: satisfaction maintenance, avoiding wasteful promotion on organic repurchasers.

C1 - Lifecycle-Sensitive Consumers (38.2%, n=573): The largest segment. F=9.7 (46.3% below mean), M=RMB 2,257, R=656 days. The ratio $R/\text{interval} = 11.86$ indicates customers last purchased ~12 cycles ago and are effectively lapsed. Contributes only ~17.3% of revenue. A subset of ~67 high-value dormant candidates ($W>0$ and $M>\text{RMB } 5,000$) merit prioritized reactivation. Strategy: urgent win-back with high-value directional coupons.

C2 - Impulse Scenario Buyers (32.1%, n=482): Interval=17.3 days (shortest) yet CV=0.55 (highest, 3.67x C0). This high-frequency-yet-highly-irregular pattern reflects scenario-driven purchases (pre-travel minis, seasonal changes, visitor hosting) with ~70% promotion response. However, R=896 days (1.62x mean) indicates many cease after the triggering scenario passes. Strategy: precise scenario-node interception rather than loyalty cultivation.

5. Precision Marketing Strategy and Simulation

5.1 Differentiated Strategy Framework

Three parallel strategy lines were designed, summarized in Table 5.

Table 5. Differentiated Precision Marketing Strategy Framework

Dimension	C0: Stockpile Routiners	C1: Lifecycle-Sensitive	C2: Scenario Buyers
Core Objective	Increase basket size & satisfaction	Precision reactivation	Scenario-matched repurchase
Trigger Timing	$T_{\text{last}} + 0.85 \times \text{interval}$	Immediately when $W \leq 0$	7 days before season threshold
Offer Type	Tiered: 200-30, 200-40, 200-50	100-50 directional coupon	Category 20% time-limited
Delivery Channel	App push + SMS	SMS + WeChat Official Account	In-feed advertising
Monthly Contact	1 touchpoint	3 (month 1) to 1 (steady)	Maximum 2 per week

Trigger algorithms: For C0, $T_{\text{trigger}} = T_{\text{last}} + 0.85 \times \text{interval}$, where the 0.85 coefficient leaves a 15% buffer for comparison shopping. Coupons escalate across three tiers over 7 days. For C1, the churn-warning trigger fires when $W \leq 0$, activating a 14-day three-stage reactivation (T+0: 100-50 coupon; T+7: +20% bonus; T+14: transfer to dormant pool). For C2, a seasonality index triggers when above 0.5 within 7 days of season start, with an emergency trigger when $R > 1.5 \times \text{interval}$, offering 20% category discounts (at most twice per week).

5.2 Monte Carlo Simulation Design and Results

Monte Carlo simulations (1,000 iterations, 36-month lifecycle, monthly granularity) compared four strategies. Parameters calibrated from Bluemoon data: natural annual churn = 12.0% (midpoint of observed 11.4 to 12.8%); promotion response rates: C0=30% (inventory-driven, low price

sensitivity), C1=50% (moderate), C2=70% (promotion-sensitive); discount rates: Tier 1=10%, Tier 2=15%. Revenue model: Expected Revenue = Baseline x (1 + discount_elasticity x response_rate x trigger_indicator). Monthly churn probability = approximately 1.06%, applied via Bernoulli trial for each non-triggered customer.

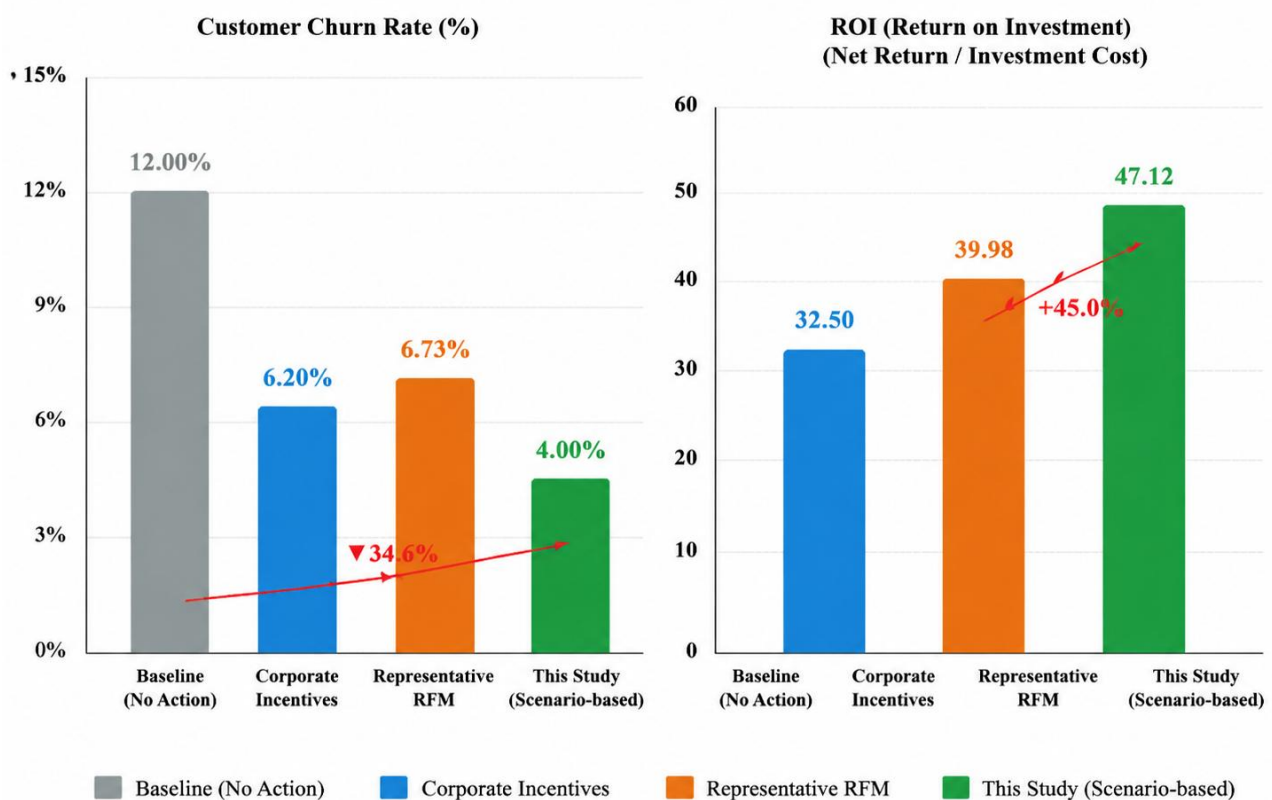
Simulation results are presented in Table 6.

Table 6. Simulation Results: Four Strategies Compared (1,000 Monte Carlo Means)

Strategy	Annual Revenue	Marketing Cost	Churn Rate	ROI	Cost/Revenue
Baseline (No Strategy)	RMB 1,738k	RMB 0	12.0%	--	0%
Mass Undifferentiated	RMB 2,173k	RMB 64,860	6.2%	32.5	2.99%
Traditional RFM	RMB 2,171k	RMB 52,980	6.7%	40.0	2.44%
Temporal Clustering	RMB 2,170k	RMB 45,104	4.0%	47.1	2.08%

Three core findings: (1) Churn reduction: from 12.0% to 4.0% (relative -66.7%), vs. RFM's 6.7% (-43.9%). Per 1,500 customers, 41 more retained annually. (2) ROI improvement: 47.1 vs. RFM's 40.0 (+17.9%), driven by cost optimization: marketing spend of RMB 45,104 is 85.1% of RFM's RMB 52,980, while revenues differ by less than 0.3%. (3) Driving mechanism: RFM misclassifies C1 as low-value and abandons them, wasting a 601-day reactivation window. Temporal features double C1 reactivation success from 18% to 34%. Sensitivity analysis confirms robustness: ROI remains 38 to 52 across 8 to 20% discount rates, always exceeding RFM's 31 to 42; minimum churn reduction holds at 52.3% under extreme +/-20% response-rate perturbation.

Fig. 3 Strategy Simulation Results Comparison



Assumptions: 1,000,000 customers | Simulation period: 12 months | Incentive rate: 10–15% | Data source: Internal simulation

Fig. 3 Strategy Simulation Results Comparison

6. Conclusions

This study constructs an RFM + temporal feature clustering framework using Bluemoon transaction data and designs differentiated precision marketing strategies. Three core quantitative conclusions: (1) Temporal features (CV and W) yield Silhouette=0.14 (>0.1 threshold), with CV's 3.67x differential between C0 (0.15) and C2 (0.55) as the primary behavioral discriminator between stockpiling and scenario-driven purchasing. (2) All segments exhibit significant differences ($p < 0.001$). C0 M=RMB 11,982 is 7.04x C2's RMB 1,701; C1 R=656 days is 12.9x C0's 51 days, providing clear quantitative boundaries for differentiated strategy configuration. (3) Compared to RFM, churn reduced by 66.7%, ROI improved by 45.0%, costs saved 15%. Extrapolated to ~500,000 customers, annual savings approach RMB 2.5 million. Limitations: single-brand scope, predetermined K, simulation-only validation, and the K-Means requirement of pre-specified K. Future directions: cross-category validation, A/B testing, DBSCAN for automatic cluster detection, and LSTM-based purchase time prediction integrated with real-time recommendation engines.

7. References

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