

User Portrait and Precision Marketing Strategy of Geographical Indication Agricultural Products Based on Improved K-means Clustering - A Case Study of JT Chuju

Jing Zhao^{1*}

¹ Chuzhou Polytechnic, Chuzhou, China

*Correspondence: Jing Zhao

Received: 13 February 2026; **Accepted:** 17 March 2026; **Published:** 20 April 2026

Abstract:

Against the backdrop of the deep integration of the digital economy and agricultural modernization, precision marketing has emerged as a pivotal pathway for geographical indication agricultural products to break through homogeneous competition and enhance industrial value. To address the issues of vague target customer positioning and inadequate strategy adaptability in the traditional marketing of JT Chuju, this study proposes an improved K-means clustering algorithm integrating feature selection and parameter optimization, and constructs a multi-dimensional user portrait system. Through questionnaire surveys, offline interviews, and e-commerce platform data collection, 486 valid sample data were obtained. After data preprocessing and feature engineering, the improved K-means algorithm was employed to achieve precise segmentation of user groups, resulting in four typical user portraits: High-Quality Social-Oriented, Dynamic Quality-Pursuing, Innovation & Quality-Focused, and Potential Low-Sensitivity. Based on these portraits, the existing problems of JT Company were diagnosed, and targeted precision marketing strategies were designed and proposed to improve its sales performance and market competitiveness.

Keywords:

User Portrait, Improved K-means Clustering, Precision Marketing

1. Introduction

JT Chuju With the in-depth advancement of the national rural revitalization and agricultural modernization strategies, the deep processing industry of characteristic agricultural products is embracing unprecedented development opportunities. As a national geographical indication product and one of Anhui Province's 'Top Ten Wan Medicines', Chuju possesses unique medicinal efficacy and profound cultural heritage, with its industrial scale expanding continuously. According to public data released by the Chuzhou Municipal People's Government, by 2024, the planting area of Chuju in Chuzhou had reached 100,000 mu, driving the total output value of the entire

industrial chain to exceed 2 billion yuan. However, the surge in the number of local deep processing enterprises has intensified market competition. Most enterprises still adhere to traditional marketing models, exhibiting prominent issues such as vague target customer positioning, severe product homogenization, and outdated promotion methods. This has directly led to an increasingly acute contradiction between diversified consumer demands and homogeneous supply, making it difficult for small and medium-sized enterprises to gain an advantage in the fierce market competition [1].

In the context of the deep integration of the digital economy and modern agriculture, data-driven precision marketing has become a key pathway for enterprises to resolve the predicament of homogeneous competition and enhance core industrial value [2]. As a core technology for in-depth excavation of consumer characteristics, user profiling has been widely applied in internet platforms, digital marketing, and other fields. By constructing a multi-dimensional user tagging system, enterprises can accurately capture consumer demand pain points and implement personalized marketing strategies [3]. Nevertheless, the practical application of user profiling technology in the field of characteristic agricultural products represented by Chuju still faces multiple practical bottlenecks: Firstly, traditional data collection methods (such as questionnaire surveys and offline interviews) have inherent limitations, including lengthy cycles and insufficient data integrity, making it difficult to comprehensively and dynamically capture user behavioral characteristics; Secondly, single clustering algorithms (such as the traditional K-means algorithm) have defects such as fixed parameters and weak scenario adaptability, resulting in user segmentation accuracy that fails to meet the actual marketing needs [4]; Thirdly, there is a disconnect between technical analysis results and commercial application scenarios, making it challenging to directly transform the technical output of user portraits into implementable and operable marketing strategy schemes.

2. Related Concepts and Research Status

2.1. Research Status of User Profiling

Foreign research on user profiling started relatively early, focusing on the innovation of technical frameworks and the exploration of cross-scenario adaptability. Alan Cooper (1988) first proposed the concept of “User Persona”, defining it as an abstract model that refines group commonalities through virtual digital means based on users’ basic information and behavioral data. In the early stage, it was mainly constructed through market research, questionnaire surveys, and in-depth interviews. With the iterative upgrading of technology, the focus of foreign research has gradually shifted to multi-dimensional feature fusion and intelligent algorithm integration. For instance, Liu (2025) constructed user portraits by integrating learners’ emotional, behavioral, and competency characteristics in the Massive Open Online Course (MOOC) scenario, providing support for personalized teaching services; Feng(2025) adopted an improved density peak clustering algorithm to build a portrait system for China’s super-new generation wine consumers, conducting in-depth exploration of the consumption characteristic differences of this group. Notably, foreign research has always attached importance to the coordinated advancement of technology implementation and privacy protection. For example, Wu(2023) constructed a privacy protection-oriented user portrait framework and applied it to personalized agricultural

knowledge service scenarios, reflecting systematic and rigorous exploration of the practical application of user profiling.

Domestic research on user profiling focuses more on refined implementation in specific scenarios and localized adaptation optimization. In the field of agricultural products, Feng(2021) systematically sorted out the application progress of user profiling technology in agricultural scenarios, clarifying that the optimization of data collection and algorithm iteration are the core development directions in the future [5]; Cai(2022) completed the construction of agricultural product consumer group portraits based on the traditional K-means clustering algorithm and proposed targeted precision marketing plans. However, existing domestic research still has obvious shortcomings: the data sources are relatively single, mostly relying on data from a single channel; the form of algorithm application is relatively simple, lacking in-depth optimization and innovation; there is a disconnect between portrait results and actual commercial application scenarios, making it difficult to directly transform them into operational strategies. Especially in the field of deep-processed characteristic agricultural products, research on the construction methods and practical application of user profiling is still relatively scarce, leaving obvious research gaps.

2.2. Research Status of Precision Marketing

Foreign research on precision marketing is driven by digital technology as the core, forming systematic achievements in model construction and technical application. Koufi. (2024) constructed an artificial intelligence-based decision-making system and explored the implementation path of precision marketing with the Moroccan market as a case study; Jiang (2022) proposed a Multi-Channel Click-Through Rate Model (MCGM) with a hierarchical gating mechanism to improve the accuracy of marketing reach. Foreign research focuses on the universality of technical logic and cross-market transfer capability, conducting in-depth studies on the application of machine learning, natural language processing, and other technologies in user demand prediction.

Domestic research on precision marketing is closely integrated with industry practice, focusing on scenario adaptation and method innovation. In the field of agricultural products, Liu (2024) pointed out that big data technology provides the underlying support for e-commerce enterprises' precision marketing in terms of user behavior analysis and demand prediction, promoting the transformation of marketing models; Wang Lu (2024) analyzed the characteristics of feed consumption behavior from the perspective of precision marketing and proposed targeted marketing strategies. However, in the field of characteristic agricultural products, there is still a lack of in-depth research on mining consumer demands and formulating personalized marketing strategies by combining user profiling technology. Most enterprises still rely on traditional marketing methods such as offline distribution and holiday promotions, resulting in low marketing efficiency.

Therefore, based on the current situation and the predicament faced by JT Company, this study intends to construct multi-dimensional user portraits through in-depth excavation and analysis of consumer data, drive precision marketing decisions, optimize the efficiency of marketing resource allocation, and ultimately achieve the goals of improving sales performance and strengthening brand competitiveness.

3. Construction and Analysis of User Portraits

3.1. Acquisition of Sample Data

The data collection for this study was completed through online questionnaire surveys. The design of the questionnaire items referred to the consumer user portrait tagging system of JT Chuju Company established earlier and drew on existing research results in the fields of user profiling and precision marketing. This questionnaire consists of three core research parts, corresponding to user behavioral attributes, user preference attributes, and user basic attributes respectively. The complete questionnaire can be found in the appendix. The formal questionnaire was mainly distributed through the Wenjuanxing platform, and offline stores of JT Chuju Company also guided on-site customers to scan the QR code to fill it out. A total of 660 questionnaires were collected, and after strict screening, 486 were determined to be valid, with an effective recovery rate of 73.6%. From the perspective of sample validity, it fully meets the research requirements and can serve as the data support for subsequent studies.

3.2. Reliability Analysis of Sample Data

Reliability testing is an important method to ensure the stability and consistency of questionnaire survey results. This study selected Cronbach's α coefficient as the core indicator to measure reliability [6]. The main function of this coefficient is to evaluate the internal consistency among questionnaire items. The higher the coefficient value, the closer the correlation among the questionnaire items, and the more reliable and stable the final measurement results, which can provide more solid data support for subsequent research and analysis. According to conventional standards, a Cronbach's α coefficient of 0.7 or higher indicates that the questionnaire reliability is within an acceptable range. In this study, all the questionnaire items designed for the Chuju product survey adopted a Likert five-point scale. The specific scoring rules are set as follows from high to low: 5 points for "Strongly Agree", 4 points for "Agree", 3 points for "Neutral", 2 points for "Disagree", and 1 point for "Strongly Disagree". The higher the score of a respondent on a certain item, the higher their degree of recognition of the statement of that item. To ensure the accuracy and reliability of the survey data, the study used SPSS statistical analysis software to systematically test the Cronbach's α coefficient of each dimension item related to Chuju products. See Table 1.

Table 1. Reliability Analysis of the Chuju Product Attention Questionnaire.

Dimension Name	Dimension Items	Cronbach's α Coefficient	Overall Scale Cronbach's α Coefficient
A:Product Dimension	A1 Tea Selection Experience A2 Segmentation of Purchase Influencing Factors A3 Consumer Demand A4 Future Expectations A5 Customer Personal Role Development	0.772	0.814
B:Price Factors	B1 One-time PurchaseB2 Bulk Purchase with DiscountB3 Special Offers, Discounts or Bundled PackagesB4 Paid Model with Regular Delivery	0.731	
C:Product Channel	C1 Importance of Convenience C2 Preference for Consumption Experience C3 Preference for Purchase	0.735	

	Channels C4 Product Discovery Methods		
D:Product Service	D1 Product Satisfaction D2 Customer Communication D3 Value-added Services D4 Professional Services D5 After-sales Service	0.912	
E:Brand Communication	E1 Attractiveness of Brand Communication Forms E2 Brand Communication Content E3 Brand Uniqueness E4 Brand Quality Perception E5 Brand Interaction Engagement	0.793	
F:Customer Preferences	F1 Lifestyle Preferences F2 Communication Method Preferences F3 New Product Trial F4 Membership Program	0.942	

Based on the statistical results in Table 1, the Cronbach's α coefficients of each dimension of the Chuju product questionnaire in this study are all higher than the critical value of 0.7, indicating good internal consistency among the items of each dimension; at the same time, the Cronbach's α coefficient of the total scale is 0.814, which further verifies that the entire questionnaire scale has high internal consistency and the data reliability reaches a reliable level. In summary, it can be determined that the questionnaire scale has high reliability, which can effectively measure the respondents' attention to Chuju products and provide reliable data support for the conduct of subsequent studies.

4. K-means Clustering Analysis

4.1. Determination of the Optimal Number of Clusters (K)

K-means clustering requires pre-determining the optimal number of clusters (K) [7]. This study combined the Elbow Method and the Silhouette Coefficient Method for dual verification to ensure the scientificity of the K value selection. The specific process is as follows: The Elbow Method determines the optimal K value by calculating the Within-Cluster Sum of Squares (WCSS) corresponding to different K values [8]. WCSS represents the sum of the squared Euclidean distances from each sample to the center of its respective cluster. A smaller WCSS indicates higher homogeneity of samples within the cluster [9]; when the K value increases to a certain critical point, the rate of WCSS decrease slows down significantly, forming an "elbow", and this critical point is the optimal K value. When K=4, the rate of WCSS decrease shows an obvious inflection point, and the curve shape is similar to an "elbow", indicating that the benefit improvement brought by increasing the number of clusters begins to slow down. Therefore, K=4 is a relatively ideal choice. Meanwhile, the average silhouette coefficients for different K values were calculated, as shown in Table 2. When K=4, the average silhouette coefficient is 0.52, which is higher than other K values, indicating that the clustering results have good intra-cluster compactness and inter-cluster separability. In summary, both methods support dividing consumers into 4 categories.

Table 2. Average Silhouette Coefficients for Different K Values.

Number of Clusters (K)	2	3	4	5	6
Calculate the average silhouette coefficient	0.45	0.48	0.52	0.47	0.43

4.2. Clustering Process and Results

In the clustering analysis of the consumer user portraits of JT Chuju Company, SPSS 26.0 software was used, and the K-means initialization method was adopted to improve algorithm stability. Iterative clustering was performed on the preprocessed data. After N iterations, the cluster centers stabilized and the model converged. The final cluster center results are shown in Table 3, which clearly displays the standardized center values of the four consumer groups on 9 characteristic variables. To test whether the differences of the four clusters in each variable are statistically significant, a one-way analysis of variance (ANOVA) was conducted in this study. The results show that all 9 clustering variables have significant differences at the 0.01 significance level ($p < 0.01$), which confirms that this clustering analysis can effectively distinguish consumer groups with distinct characteristics, and the clustering effect is ideal [10].

Table 3. Final K-means Clustering Center Results.

Selection of characteristic variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Analysis of Variance (p-value)
different age groups	0.85	-0.12	0.15	1.82	0.000
Gender	0.33	0.37	0.42	0.08	0.000
Monthly Income	0.45	0.72	1.25	-0.15	0.000
Occupation	0.68	0.78	0.35	-0.45	0.000
Educational Background	0.55	0.67	0.62	-0.95	0.000
Purchase Motivation	1.12	1.18	-0.35	-1.02	0.000
Price Factor	-1.02	-0.88	1.53	-1.15	0.000
Purchase Channel	0.32	1.26	1.15	-1.45	0.000
Psychological Preference	0.92	1.58	1.72	-1.35	0.000

The user group in Cluster 1 can be defined as “High-Quality Social-Oriented” users. This group has high scores in “Monthly Income” (0.45), “Occupation” (0.68), and “Purchase Motivation” (1.12), indicating that they have a good socioeconomic status and strong consumption motivation, with a particular emphasis on social gifting. At the same time, their score in the “Price Factor” is a significant negative value (-1.02), far below the average level, indicating that they are extremely insensitive to price and value the social value brought by products more.

The user group in Cluster 2 can be defined as “Dynamic Quality-Pursuing” users. This group has the highest scores in “Purchase Channel” (1.26) and “Psychological Preference” (1.58), showing their strong acceptance of diversified shopping channels and positive product attitudes. Their “Age Group” (-0.12) and “Price Factor” (-0.88) are close to or slightly below the average level, depicting a portrait of a young, active group that values cost-effectiveness.

The user group in Cluster 3 can be defined as “Innovation & Quality-Focused” users. This is the most distinctive group, with the highest scores among the four categories in “Monthly Income” (1.25), “Educational Background” (0.62), “Price Factor” (1.53), and “Psychological Preference” (1.72). This indicates that they have the strongest purchasing power and are willing to pay a premium for high quality,

innovation, and excellent experiences, making them typical rational and highly educated consumers.

The user group in Cluster 4 can be defined as “Potential Low-Sensitivity” users. This group has negative values in most variables, especially far below the average level in “Educational Background” (-0.95), “Purchase Motivation” (-1.02), “Purchase Channel” (-1.45), and “Psychological Preference” (-1.35). This indicates that their awareness, interest, and purchase intention towards Chuju are all very low, with passive consumption behavior, making them potential users that need to be cultivated through low-threshold strategies.

5. Generation of User Portraits Based on Clustering Analysis

Based on the collection, cleaning, and analysis of user data, and using the K-means algorithm to construct user portraits, the customer groups of JT Chuju Company are mainly divided into four categories: High-Quality Social-Oriented, Dynamic Quality-Pursuing, Innovation & Quality-Focused, and Potential Low-Sensitivity.

The essence of the consumption behavior of High-Quality Social-Oriented users is to realize the transmission of social value through JT Chuju. Their demands can be summarized as guaranteed quality, distinctive brand image, and decent gifting value. As the core customer group in the high-end market of JT Chuju, this group plays a key role in shaping the brand’s premium capacity and market reputation, and is a high-value user group that enterprises need to focus on maintaining.

The essence of the consumption behavior of Dynamic Quality-Pursuing users is to achieve health management in fragmented scenarios through convenient Chuju products. Their demands can be summarized as small packaging for easy carrying, time-saving online purchasing, and reasonable prices without feeling distressed. They do not pursue the social added value of products, but are highly sensitive to whether they are suitable for living scenarios and in line with health concepts. They are the core target for brands to break through the young market through scenario-based innovation.



Figure 1. Word Cloud of Portrait Characteristics of the Four Groups.

The essence of the consumption behavior of Innovation & Quality-Focused users is to construct an exquisite lifestyle that conforms to their self-aesthetics through rationally chosen innovative products. Their demands can be summarized as rejecting

mediocrity and gimmicks, pursuing the dual combination of innovative forms and solid quality, as well as the alignment between products and their own tastes and values.

The essence of the consumption behavior of Potential Low-Sensitivity users is low-risk trial. Their demands are mainly reflected in occasionally buying a little if the price is cheap; but there is no need to spend time understanding, nor to expect special effects. Such users are in an edge state of knowing but not understanding, having bought but not being loyal. For JT Chuju, the conversion of this group needs to break through cognitive barriers and decision-making inertia, and gradually cultivate consumption habits through low-price incentives to reduce the trial threshold.

6. Optimization of Precision Marketing Strategies

6.1. Precision Marketing Strategy for High-Quality Social-Oriented

Users According to the user portrait results, when purchasing Chuju products, High-Quality Social-Oriented consumers' consumption motivation is highly focused on social scenario needs. From the perspective of consumption behavior characteristics, such consumers generally have a high single customer price, and their purchase time shows significant periodicity. Such customers pay more attention to the popularity and quality of Chuju products.

High-Quality Social-Oriented consumers purchase Chuju products mainly based on social motivations such as business interactions, workplace needs, and relationship maintenance. Such customers usually show bulk purchase characteristics and have high requirements for product brand reputation and quality standards. In view of the consumption characteristics of this group, enterprises need to shape a high-end brand image, highlight the quality advantages and grade differences of products, develop high-end gift packaging that meets the needs of business scenarios, and launch customized Chuju product series specifically for business activities and social gifting.

6.2. Precision Marketing Strategy for Dynamic Quality-Pursuing Users

According to the user portrait results, the core purpose of Dynamic Quality-Pursuing users purchasing Chuju products is daily personal consumption. Their demand focus is on the convenience and health attributes of products; from the perspective of consumption behavior, such users have a high purchase frequency, significant dependence on online platforms, and higher acceptance of new Chuju categories and forms than other consumer groups. Therefore, for Dynamic Quality-Pursuing users who pursue convenient health and digital experiences, it is necessary to construct a strategy combination featuring scenario-based solutions and efficient channels.

When purchasing Chuju products, Dynamic Quality-Pursuing consumers first pay attention to convenience and health attributes, and tend to choose products that adapt to fast-paced living scenarios. As a daily health-preserving drink, in busy work and sports, consumers value the ready-to-drink nature and clear functionality of products more. However, traditional bulk Chuju requires self-brewing and difficult dosage control, which is difficult to meet their efficiency needs. Therefore, merchants should develop "portable cold-brew tea bags", independent small packages, supporting cold water instant dissolution, and "Chuju + Lemon" compound blended packages, with scientific proportioning to simplify the matching steps, and label functional tags such

as “zero additives” and “suitable for post-stay-up/sports”, directly hitting their core demand of “balancing health and efficiency” through scenario-based design.

6.3. Precision Marketing Strategy for Innovation & Quality-Focused Users

According to the user portrait results, when purchasing Chuju products, Innovation & Quality-Focused consumers’ core attention is focused on the uniqueness and design sense of products, and they tend to choose innovative categories that break through traditional forms. Such users have the willingness to pay a premium for product quality and creative culture, pursuing the dual adaptation of innovative forms and solid quality, as well as the alignment between products and their own aesthetic tastes and value propositions. Therefore, for Innovation & Quality-Focused users who favor innovative design and extreme quality, a strategic path focusing on product leadership and in-depth interaction is planned.

When purchasing Chuju products, Innovation & Quality-Focused consumers first pay attention to uniqueness and design sense, and tend to choose innovative products that break through traditional forms. Their definition of quality not only includes raw materials, but also creative concepts and cultural expression. However, traditional Chuju products have a single form, which is difficult to meet their personalized needs. Therefore, merchants can launch “Chuju +” cross-border products: cooperate with aromatherapy brands to develop “Chuju soothing aromatherapy”, co-design “solar term-themed tea set sets” with cultural and creative brands, and even launch “edible Chuju petals” to adapt to baking and bartending scenarios, endowing products with trial value through form innovation, while retaining the “intangible cultural heritage craftsmanship” core as quality endorsement.

6.4. Precision Marketing Strategy for Potential Low-Sensitivity Users

According to the user portrait results, Potential Low-Sensitivity consumers have a medium income level and a generally popular consumption level. When purchasing Chuju products, price factors are the primary decision-making basis. Such users have a shallow understanding of Chuju products, with low purchase frequency and customer unit price, high dependence on offline supermarkets for purchase channels, and their purchase behavior is mostly triggered by promotional activities such as supermarket discounts. Therefore, for Potential Low-Sensitivity users who are price-sensitive and have a low level of cognition, a strategy plan targeting low-threshold reach and value awakening is designed.

When purchasing Chuju products, Potential Low-Sensitivity consumers take price factors as the primary decision-making consideration and tend to choose simple, burden-free basic models. Such users have a shallow understanding of Chuju, worry about uncomfortable taste or additives, and need a low-risk initial experience. For such consumers, first of all, when providing products and services, JT Company should simplify product choices, reduce user decision-making difficulty through clear product classification and clear price levels, and help them complete purchases quickly. Secondly, merchants should develop “entry-level tasting packages”, including small-dose traditional Chuju and mild blended versions, labeled “zero sulfur fumigation” and “beginner-friendly”, and attached with third-party quality inspection reports, focusing on marking pesticide residue and additive test results, and reducing their safety concerns through “transparent ingredients”. Finally, combined with the communication characteristics of short video platforms, clearly convey the product’s value proposition through scenario-based content.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

Funding

This article is Chuzhou Polytechnic ‘Parallel Computing-Driven Architecture and Application Research of Intelligent Traffic Perception Systems (Project No.: ZKY-2025-8)’ achievement.

References

- [1] Dong, S. Application Research of Multi-Dimensional Customer Behavior Analysis Model in Precision Marketing. *Open Journal of Applied Sciences*, 2024, 14(12), 3589-3600.
- [2] Duan, J. Research on Precision Marketing Model of Enterprise Market under the Background of Digital Finance. *Computer Informatization and Mechanical System*, 2024, 7(5), 79-81.
- [3] Feng, Y.; Mu, W; Li, Y, et al. User profiling for Chinese super-new generation wine consumers based on improved density peak clustering algorithm. *Kybernetes*, 2025, 54(6), 3267-3295.
- [4] Golalikhani, M; Oliveira, B.B; Correia, A.D.H.G, et al. Optimizing multi-attribute pricing plans with time- and location-dependent rates for different carsharing user profiles. *Transportation Research Part E*, 2024, 192, 103760.
- [5] Feng, J.Y; Wang, B; Wu, D.D, et al. Research Progress of User Portrait Technology and Its Application in the Agricultural Field. *Transactions of the Chinese Society for Agricultural Machinery*, 2021, 52(S1), 385-395.
- [6] Fan, M.X, Wang, J.X. User Portraits, Usage Behavior and Motivation of Book Podcasts — An Analysis Based on In-Depth Interviews and Questionnaire Surveys. *Chinese Editors Journal*, 2024, 12, 52-59.
- [7] Hu, Q. Analysis of Precision Marketing and Consumers’ Online Shopping Behavior from the Perspective of Perceived Value and Perceived Risk. *Journal of Commercial Economics*, 2021, 13, 71-74.
- [8] Hong, W.M. The Orientation of Personal Information and the Transformation of Precision Marketing Model in the Big Data Era. *Social Scientist*, 2019, 02, 114-120.
- [9] Li, W.R, Wen, T.X. A Review of Domestic and Foreign Research on User Portraits. *Information Research*, 2024, 01, 119-126.
- [10] Li, X.Y.; Zhou, D.T. A Dynamic Weighting Statistical Method for Questionnaires Based on K-means Clustering. *Statistics & Decision*, 2018, 34(23), 80-83.



© 2026 by the author(s); licensee International Technology and Science Publications (ITS), this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (<http://creativecommons.org/licenses/by/4.0/>)