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Research on Logistics Distribution Network Optimization and Service Model Innovation for Rural E-commerce

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SUMMARY: *Optimizing the logistics distribution network for rural e-commerce holds significant importance for promoting economic growth. This paper proposes an urban logistics distribution model to achieve an efficient, low-consumption rural logistics innovation service model. Subsequently, it combines regression analysis, factor analysis models, and k-means clustering to optimize the logistics distribution network for rural e-commerce. Taking County S as a case study, the results show that the average scores for villages and towns in "Cluster-1," "Cluster-2," and "Cluster-3" are 2.6, -0.24, and 0.27, respectively. Among these, Cluster-1—TC Town and LX Town—achieve the highest scores. Priority should be given to the layout of logistics network nodes in these areas to improve logistics organizational structures and drive the efficient development of rural logistics.*

KEYWORDS: *k-means; factor analysis; ridge regression analysis; distribution network; rural e-commerce*

1 Introduction

The development of rural e-commerce has become a vital component of China's e-commerce landscape. Optimizing logistics distribution networks can better meet consumers' growing demands, enhance user experience, and promote the healthy development of e-commerce [1-3]. Literature [4] reveals, through an illustrative case study of three Chinese villages, the significant role of information and communication technologies—particularly e-commerce—in advancing development in remote areas. It discusses current challenges facing rural e-commerce development and offers recommendations. Reference [5] introduces the development and challenges of rural e-commerce, examines the logistics distribution chain using the traveling salesman problem model, and identifies optimal delivery routes through research. Currently, rural e-commerce logistics networks still face issues, primarily manifested in difficulties with last-mile delivery and low delivery efficiency [6, 7]. Literature [8] elaborates on challenges in rural e-commerce, including language barriers, trust issues, security concerns, and legal complications, aiming to provide guidance for practitioners. These obstacles constrain rural e-commerce growth and dampen consumer purchasing intent [9]. To address bottlenecks in rural e-commerce logistics networks, strategies such as collaborative network development, logistics informatization, and optimized last-mile delivery services can be adopted [10-12]. Establishing a comprehensive, efficient, and stable delivery system enables deep collaboration with logistics enterprises, express delivery companies, and rural logistics service stations to jointly improve the distribution network

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[13-15]. Advancing logistics informatization is crucial for enhancing rural e-commerce delivery efficiency [16]. Literature [17] analyzes the importance of mobile e-commerce for informatization development based on current conditions and researches pathways to elevate rural mobile e-commerce. Information technology enables automated order sorting, optimized route planning, and real-time logistics tracking, thereby boosting delivery efficiency and reducing costs [18, 19]. Literature [20] describes the role of information technology (IT) in logistics operations and explores how IT applications and capabilities impact logistics service providers' performance and competitiveness. Interview findings indicate that corporate performance and competitive advantages are significantly influenced by IT adoption. To optimize last-mile delivery services, new technologies like drones and smart parcel lockers can be introduced to enhance delivery efficiency and reduce transit times [21, 22]. Literature [23] examines the long-term impacts of e-commerce's growing significance, particularly the effects of transitioning to drone parcel delivery models. It employs a multi-center city spatial general equilibrium model integrating diverse retail channels to simulate consumer decision-making between physical and online shopping.

Beyond the logistics distribution network, rural e-commerce logistics services also face several challenges [24]. First, service levels remain low, delivery times are lengthy, and services are often untimely [25]. Reference [26] developed a hybrid logistics service quality assessment model based on a BP neural network, and through empirical analysis, validated the practical effectiveness of this BP-based evaluation model for rural e-commerce logistics services. Reference [27] developed a rural e-commerce logistics service quality assessment system using a specific enterprise as a case study. Surveys and questionnaires conducted among local residents revealed varying levels of e-commerce logistics service quality, leading to proposed strategies for improving rural e-commerce logistics service quality.

Second, the lack of effective cooperative mechanisms hinders the provision of targeted logistics services, severely impeding the development of rural e-commerce [28-30]. Reference [31] aimed to determine the impact of specific logistics service dimensions on product satisfaction within the e-commerce industry. Based on survey findings, it indicated that product availability, delivery time, and shipping costs had limited influence on satisfaction, while product quality exerted a significant and positive effect. Furthermore, innovation in rural e-commerce logistics services enhances competitiveness and market influence, providing rural residents with more convenient and efficient shopping experiences [32-34]. Literature [35] offers insights into how service innovation influences e-commerce customer behavior, providing references for enhancing customer experience management and decision-making in last-mile e-commerce service management. Furthermore, logistics service innovation can stimulate rural market prosperity and support the transformation and upgrading of the rural economy [36]. Achieving innovation in rural e-commerce logistics services requires establishing robust logistics information systems to enhance traceability and transparency of logistics data. Concurrently, intensified efforts in cultivating rural e-commerce logistics talent are essential to elevate the professional standards of logistics services [37-40].

This paper summarizes the current status and challenges of rural logistics distribution in Zhejiang Province, advocating for the development of an efficient, low-consumption rural logistics innovation service model. Using a ridge regression model to forecast rural regional logistics volume, it verifies the necessity of constructing rural logistics distribution centers. Subsequently, principal component extraction identifies factors influencing distribution center site selection. Comprehensive scores for each township in County S are calculated, serving as the basis for classifying township importance using k-means clustering. This process selects optimal site locations, thereby enhancing rural logistics distribution efficiency and reducing costs in Zhejiang. Finally, based on an analysis of County S's current development status, this paper conducts empirical research to explore the practical effectiveness of ridge regression analysis, factor analysis models, and k-means models in optimizing rural logistics networks.

2 Research on Innovative Models for Rural Logistics Distribution Services

2.1 Rural Logistics Distribution Challenges

With the rapid development of China's e-commerce, the logistics industry has become an indispensable part of our lives. The advanced express delivery sector and comprehensive market structure have become crucial safeguards for modern rural economic development. However, from a historical perspective, while the industrial status of rural logistics has gradually been established, its sector boundaries have become increasingly blurred, resulting in a complex and intricate market landscape. Academic circles harbor significant debate regarding the definition and characteristics of the logistics industry. To comprehensively understand issues related to rural logistics distribution, this paper focuses on rural e-commerce as its primary research subject. By reviewing historical materials and analyzing relevant statistical data, it conducts a comprehensive analysis of existing problems in rural logistics distribution. Comparing this with urban logistics distribution and employing research methods such as comparative analysis and data analysis, accurately grasping the development trends and influencing factors of rural logistics distribution. The key to resolving rural logistics distribution issues lies in comprehensively advancing an integrated rural distribution system. With “high efficiency and low consumption” as the goal and ensuring the effective operation and sustainable development of the rural logistics industry as the core, we vigorously promote a development model where urban areas drive rural areas. This further improves and perfects the rural circulation system, enabling rural logistics distribution to develop in a scaled, specialized, standardized, and informatized manner, thereby enhancing logistics distribution efficiency and reducing costs.

(1) Lagging rural regional logistics infrastructure. As a second-tier region, Zhejiang faces rapid growth in express delivery volume while grappling with challenges such as limited space for township delivery points, restricted vehicle access, and extended delivery distances—all manifestations of underdeveloped rural infrastructure.

(2) Dispersed rural delivery areas and high logistics costs. Rural logistics distribution currently represents the most significant shortfall in China's delivery system development. This stems primarily from rural areas' vast expanses with sparse populations, resulting in scattered delivery zones, low resource utilization, difficulty in consolidating goods, and end-point outlets facing high investment and per-unit costs.

(3) Low levels of informatization and standardization, preventing resource sharing. Despite expanding rural network coverage in recent years, information standardization levels remain inadequate. No integrated service platform exists between rural and urban logistics for information sharing, inventory control, or unified distribution. Consequently, shared logistics resources—including information, facilities, transportation, and human capital—cannot be optimally allocated. Low utilization of rural distribution resources prevents centralized delivery, significantly reducing logistics efficiency.

(4) Significant disparities exist in rural delivery standards, and the rural joint delivery system remains underdeveloped. Rural economic development and consumer spending levels lag far behind urban areas. Farmers lack awareness of online consumption, and rural logistics development has not received sufficient attention. Consequently, logistics delivery standards

in most rural areas of Zhejiang Province are relatively backward compared to urban areas.

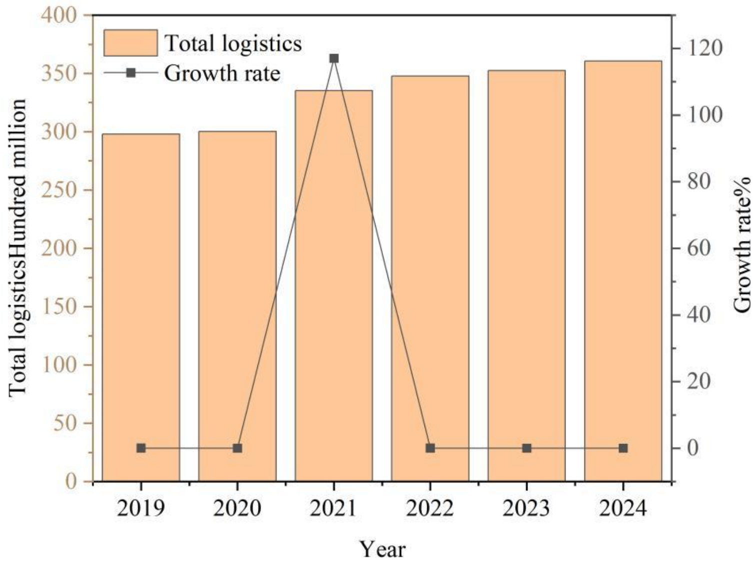
(5) Shortage of specialized talent. Compared to urban resources, remote rural areas face a shortage of working-age labor, and logistics professionals are even scarcer. Moreover, logistics enterprises in these areas are often newly established, small-scale, and staffed predominantly by young workers whose capabilities and experience remain inadequate. Although comprehensive higher education and professional training systems exist for transportation, warehousing, handling, and distribution services, rural areas neglect cultivating personnel with specialized logistics expertise. Some enterprise leaders subjectively view employees as cheap labor, leading to flawed internal human resource evaluation systems. where employees possess relevant technical skills yet lack corresponding recognition and promotion opportunities. This results in significant attrition of personnel with specialized logistics knowledge. To address the numerous challenges in rural logistics distribution, cultivating enterprise talent is crucial.

2.2 Current Status of Rural Logistics and Total Social Logistics Volume

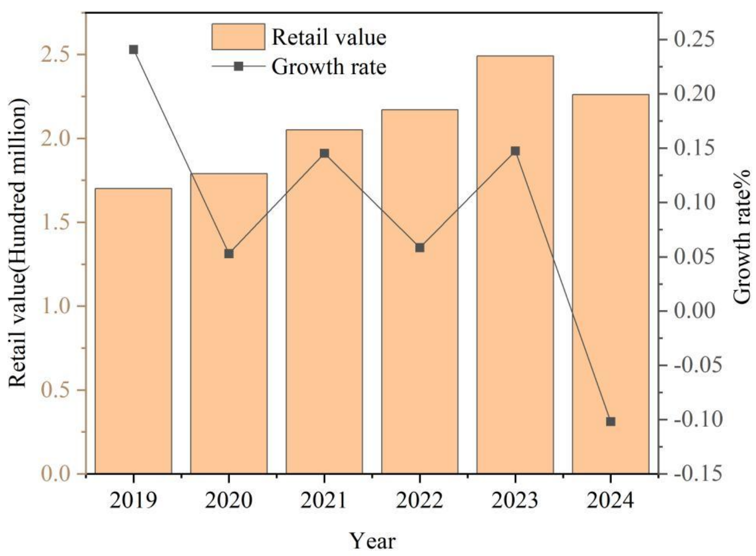
Rural logistics constitutes an integral part of rural economic activities, encompassing a series of logistics operations conducted in rural areas such as procurement, storage, transportation, distribution, and related information processing. Against the backdrop of China's accelerated rural revitalization strategy, the efficient operation of rural logistics has become a pivotal link connecting rural production with urban consumption, maximizing the value of agricultural products, and promoting rural socioeconomic development. With the widespread adoption of internet technology and the growth of e-commerce, e-commerce platforms have penetrated rural markets, opening new sales channels for agricultural products and driving increased demand for rural logistics. However, the inadequacy of rural logistics systems hampers the development of rural e-commerce and the rural economy, impacting agricultural product prices and farmers' income levels. To meet the new demands of rural economic development in this era, rural logistics must optimize network layouts, fully leverage its role in promoting rural economic growth, overcome existing challenges, and drive the diversified development of the rural economy.

With the acceleration of economic globalization and marketization, the logistics industry—a vital component of the modern economic system—has experienced rapid growth. Data released by the China Logistics Information Center is shown in Figure 1.

In 2024, the national social logistics volume reached approximately 360.6 trillion yuan. The implementation of the rural revitalization strategy has injected new vitality into rural economic development, propelled the growth of rural e-commerce, and facilitated the transformation and upgrading of the logistics industry. According to data from the National Bureau of Statistics, China's rural online retail sales reached approximately 2.56 trillion yuan in 2024.



(a) Total social logistics



(b) Online retail sales in rural areas

Figure 1: Total national social logistics

2.3 Research on Innovation in Delivery Service Models

First, establish an integrated rural e-commerce platform system. Utilizing the "Postmaster" system as an O2O channel, create a comprehensive rural e-commerce service platform centered on functions such as wholesale goods, offline purchasing services, inventory management, membership administration, and community services. Integrate existing rural postal information systems to achieve a unified interface. and one-click login. By connecting to third-party platforms, it enables proxy purchasing and collection/payment services. Internally, it links with business operations, customer management, and delivery systems to facilitate sorting, settlement, customer management, small parcel delivery, and self-pickup.

Second, establish rural e-commerce service operation centers. In terms of construction planning, leverage existing facilities and establish centers in county seats and major townships. Functionally, these centers will serve as demonstration hubs for operational models, product showcases, transaction settlements, technical support, after-sales services, personnel training, and warehousing/distribution—all aimed at enhancing the postal service's rural e-commerce brand image and societal influence.

Third, advance the construction of an integrated rural co-delivery system. First, address new demands in e-commerce delivery. Rural delivery networks are characterized by numerous points and extended routes, with logistics challenges long hindering e-commerce development. Advancing this integrated system requires leveraging the postal service's existing delivery infrastructure. Enhancing rural logistics capacity through measures like adding vehicles and increasing delivery frequency will ensure seamless integration and rapid transfer of rural mail across all network tiers. This system should serve as a vital platform for distributing agricultural products—particularly for decentralized distribution—comprehensively addressing core challenges like "the first mile out of rural areas" and "the last mile into rural areas" that hinder rural e-commerce growth. Second, the postal service's rural last-mile delivery network can be fully opened to social channels, allowing private express and logistics companies to leverage this platform to enter and exit rural areas.

The rural logistics distribution system for rural e-commerce is planned and developed based on an understanding of the foundational framework, coverage scope, and operational objectives for efficient rural delivery. It should align with rural economic development trends, integrate urban logistics models without disrupting rural character or existing patterns, and organically connect urban modernization with rural modernization. This requires coordination among rural logistics components, optimization of logistics resources, and real-time tracking of logistics information to ensure bidirectional flow within distribution channels, thereby forming an efficient, low-consumption rural logistics distribution system as illustrated in Figure 2.

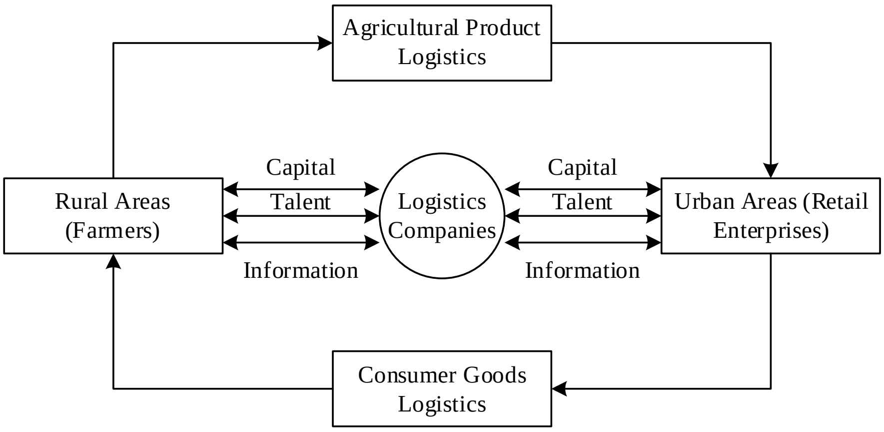


Figure 2: logistics distribution resource flow chart

3 Construction of an Optimization Model for Rural Logistics Networks

Regarding the location selection problem for logistics distribution centers in optimizing rural e-commerce logistics networks, commonly used quantitative analysis models include the centroid method, Baumol-Wolfe model, and p-median model. All these models aim to minimize costs as the optimal objective. This paper first employs a ridge regression model to forecast regional logistics volume, thereby substantiating the necessity of constructing rural e-commerce logistics distribution centers. Subsequently, it combines factor analysis with the k-means clustering model to enhance the representativeness of each indicator. The comprehensive village-town scores derived from factor analysis serve as the data foundation for k-means clustering. These scores provide a holistic evaluation of villages and towns within the region, facilitating the optimization of site selection outcomes.

3.1 Ridge Regression Analysis

Ling regression analysis is an enhanced version of the least squares method. Analyzing it from the perspective of the general linear regression equation system, we derive $\beta = (X \; X)^{-1} X \; Y$ from $X\beta = Y$, where $X^{'}$ denotes the transpose matrix of X. When performing least squares estimation, it is generally assumed that the matrix X is full rank, i.e., $\left|X^{'}X\right| \neq 0$. When $\left|X^{'}X\right| = 0$, the matrix β obtained through least squares estimation will exhibit significant error. Due to multicollinearity, the matrix X is not full rank, i.e., $\left|X^{'}X\right| = 0$. Therefore, this paper constructs the matrix $X \; X + KI$ to reduce errors, where I is the identity matrix and k>0.

Here, k is the ridge regression parameter. From the matrix form of the least squares method, the distinction between ridge regression and ordinary least squares lies in the shrinkage of estimated coefficients toward zero. Given a response vector $y \in IR^{n}$ and a prediction matrix $y \in IR^{n*p}$, the ridge regression coefficients are defined as:

$$\beta = (X^{'}X + KI)^{-1} X^{'}Y \tag{1}$$

After constructing the new matrix, it is necessary to analyze the ridge regression parameters. When selecting the k value, the ridge trace method is generally employed. The ridge trace method is a technique for selecting appropriate ridge regression parameters by analyzing the relationship between k and β(k). The β value changes with the k value. When selecting k, attention should be paid to choosing the k value at which β remains stable [41].

3.2 Factor Analysis Method

Factor analysis is a multivariate statistical method that starts from the internal dependencies within the correlation matrix of research indicators. It reduces variables with overlapping information and intricate relationships to a small number of independent composite factors. The fundamental concept involves grouping variables based on the magnitude of their correlations, ensuring that variables within the same group exhibit high correlations while those in different groups are uncorrelated or show low correlations. Each group of variables represents a basic structure, namely a common factor. This method can eliminate correlations among the original indicators while retaining most of their original information, reconstructing new interpretable common factors. Simultaneously, it yields the weights of each indicator, objectively reflecting the relative importance among them [42].

The mathematical model of factor analysis assumes that the observation system (i.e., the evaluation population) comprises m evaluation indicators and p observation units. This model expresses each of the p observation units as a linear weighted sum of $m < p$ common factors and one unique factor, as follows:

$$\begin{bmatrix} X_1 \\ X_2 \\ \\ X_p \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \\ \mu_p \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2m} \\ \alpha_{p1} & \alpha_{p2} & \cdots & \alpha_{pm} \end{bmatrix} \begin{bmatrix} F_1 \\ F_2 \\ \\ F_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \\ \varepsilon_p \end{bmatrix} \tag{2}$$

In the equation: $F_1, F_2, \cdots F_m$ are common factors, unobservable variables. They represent factors common to all indicators, typically independent of one another; The coefficient α_{pm} represents the coefficient of the p th variable on the m th common factor, referred to as the factor loading. It reveals the relative importance of the p th variable on the m th common factor. ε_i is the factor unique to each corresponding variable X_i, termed the specific factor, representing the portion not contained within the preceding m common factors. They satisfy:

$$\operatorname{cov}(F, \varepsilon) = 0 \tag{3}$$

$$D(F) = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{bmatrix} = I \tag{4}$$

$$D(\varepsilon) = \begin{bmatrix} \sigma_1^2 & & & \\ & \sigma_2^2 & & \\ & & \ddots & \\ & & & \sigma_p^2 \end{bmatrix} \tag{5}$$

In the formula: F and ε are uncorrelated. $F_1, F_2, \cdots, F_m$ are mutually independent and have variance 1. $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_i$ are mutually independent, with variances not necessarily equal; typically assumed to follow $\varepsilon_i N\left(0, \sigma_i^2\right)$.

3.3 K-means Clustering Algorithm

The K-means algorithm is an unsupervised clustering method primarily designed to automatically group similar samples into categories. It finds applications across various fields, including biology and image processing. However, clustering algorithms are often susceptible to the “curse of dimensionality,” rendering them unsuitable for high-dimensional scenarios. Therefore, this paper combines factor analysis with clustering algorithms. Factor analysis effectively reduces data dimensions while preserving as much meaningful information as possible. When integrated with clustering algorithms, it enables both data classification and dimensionality reduction [43]. This paper employs the stepwise classification method to determine the number of clusters, with the specific application steps outlined below.

Step 1: Input the original dataset X. Select k centroids, denoted as $u_1, \cdots, u_k \in R^n$, where $X = \{x_1, x_2, \cdots, x_m\}$ and $x_j \in R^n, i = 1, 2, \cdots, m$.

Step2 Calculate the Euclidean distance between each sample x_j in dataset X and its nearest centroid u_j. Assign sample x_j to the cluster containing its nearest centroid. The calculation formula is:

$$C_j = \arg\min \left\| x_j - u_j \right\|, C_j = j = 1, \cdots, k \tag{6}$$

Step 3: Continuously update the centroids of the k sets:

$$u_j = \frac{\sum_{i=1}^{m} x_i \left| c_i - j \right.}{\sum_{i=1}^{m} 1 \left| c_i - j \right.} \tag{7}$$

Step 4: Repeat Steps 2–4 until the center of mass remains essentially unchanged.
Step 5: Assign the k sets of data points to k clusters.

4 Case Study on Rural Logistics Node Site Selection in County S

4.1 Current Development Status of County S

In 2024, the county achieved an urbanization rate of 40%, with a regional GDP of 37.984 billion yuan and an urban per capita disposable income of 34,912 yuan, demonstrating pronounced economic characteristics in the county seat. A preliminary “two horizontal, two vertical” main transportation network has been established, with a total highway mileage of 3,290 kilometers. Concurrently, S County continues to enhance rural road construction, having essentially achieved road connectivity to every village. S County holds a crucial position within its city's logistics system, serving as a core hub. However, the county operates only one logistics distribution center responsible for the county seat's cargo consolidation and distribution, which cannot meet the growing demands of S County's logistics market.

4.2 Site Selection for Rural Logistics Nodes in County S Based on the k-means Algorithm

The most critical metric in logistics node site selection is logistics volume demand. The magnitude and distribution of demand serve as the foundation for establishing logistics nodes. Therefore, the first step involves forecasting logistics demand in County S. The following indicators were identified: Gross Domestic Product: X1 Total Retail Sales of Consumer Goods: X2 Per Capita Disposable Income: X3 Total Postal Business Volume: y Statistical data is presented in Table 1.

Table 1: Regression prediction statistics

Year	Gross product (Hundred million)	Total retail sales of consumer goods (Hundred million)	Per capita	Collect (Hundred million)
2018	178.4	100.6	21616	1.1
2019	192.3	121.6	23756	1.18
2020	205.5	136.2	25206	1.24
2021	223.7	142.1	27309	1.33
2022	246	159.5	29575	1.5
2023	270.1	178	32018	1.5
2024	380	198.4	34912	1.77

The analysis of variance is shown in Table 2. Using statistical data for ridge regression analysis, the significance level of the ANOVA was 0.045 < 0.05, indicating that in this analysis, there exists a significant linear relationship between the three variables and logistics demand volume.

Table 2: Variance analysis table

	Sum of squares	df	Mean square	F	P value
Regression	0.335	4	0.114	11.784	0.045
Residual error	0.029	4	0.009		
Total	0.359	8			

The R-squared values remained above 85% both before and after adjustment, indicating that the regression model demonstrates good fit. The results are shown in Table 3. Based on the statistical indicators in Table 1, the independent variables exhibit an upward trend. Combined with the regression equation, this suggests that logistics demand in County S will also grow over the next three years, providing support for the next phase of site selection.

Table 3: Regression prediction

	Nonnormalized coefficient		Normalization factor	t	p
	B	Standard error	Beta		
Constant	0.142	0.146	-	0.953	0.417
Per capita disposable income	0.002	0.001	0.278	5.845	0.012
Gross product	0.002	0.001	0.234	4.247	0.026
Society	0.004	0.000	0.269	5.572	0.017

Step two: Employing a single exponential smoothing method, we forecast 2024 indicator data for each township based on five-year historical metrics including GDP, urban area, population density, number of national/provincial highways, and logistics volume. We then analyzed the explanatory variance capacity of influencing factors: the primary factor contributed 59.212%, with the second principal factor contributing 20.648%. Together, these two principal factors explain 79.897% of the variance. The principal component score matrix is presented in Table 4.

Table 4: Variance specification table

	Constituent	
	1	2
Gross product	0.913	0.256
Urban area	0.611	-0.396
Population density	0.952	0.154
The number of highway lines in the country	-0.263	0.889
Physical flow	0.911	0.107

Let GDP be denoted as X1, urban area as X2, population density as X3, number of national and provincial highways as X4, and logistics volume as X5. Applying linear transformation according to the formula yields:

$$F1 = 0.000003524 \times X_1 + 0.007614 \times X_2 + 0.00001496 \times X_3$$
$$- 0.1853 \times X_4 + 0.009347 \times X_5 - 1.346$$
$$F1 = 0.000002745 \times X_1 + 0.0140 \times X_2 + 0.000006879 \times X_3$$
$$- 0.1835 \times X_4 + 0.003145 \times X_5 - 0.2451$$

The impact factors of each index are calculated according to the two tables, and the results are shown in Table 5, the composition impact factor table.

Table 5: Component impact factor table

Index	Factor	Index	Factor
Gross product	0.62	The number of highways in the province	0.04
Urban area	0.29	Logistics injection	0.58
Population quantity	0.60		

The cluster distribution map reveals the specific distribution patterns of the three clusters. The horizontal axis "Total Score" represents the aggregate score of all villages and towns within a specific cluster. The vertical axis "Frequency" indicates the frequency distribution corresponding to each value of the clustering variable, as shown in Figure 3. For instance, "Cluster-1" indicates that the average score of villages and towns within this cluster is 2.6, with the lowest corresponding frequency—meaning this cluster contains the fewest villages and towns among the three categories.

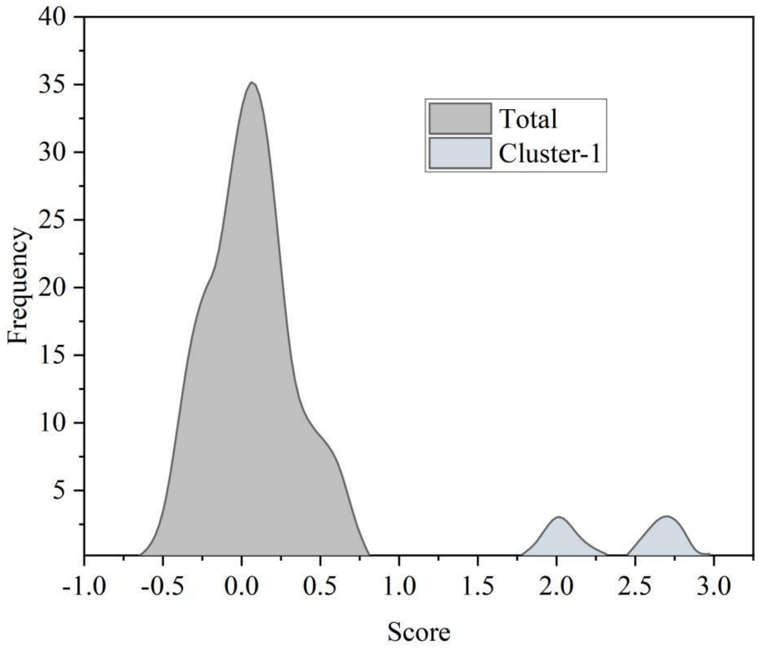


Figure 3: Cluster-1 distribution

The Cluster-2 distribution is shown in Figure 4. The average score for villages and towns in "Cluster-2" is -0.24, with the highest frequency in the entire dataset. This cluster contains the largest number of villages and towns among the three categories.

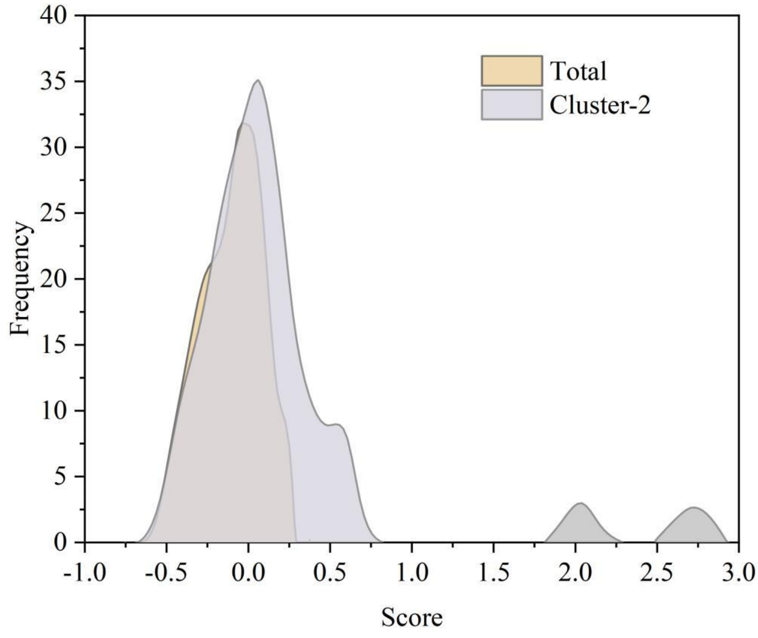


Figure 4: Cluster-2 distribution

The distribution of Cluster-3 is shown in Figure 5. The average score for villages and towns in Cluster-3 is 0.27, corresponding to a frequency that places it in the middle of the overall distribution. This cluster comprises 30% of all villages and towns.

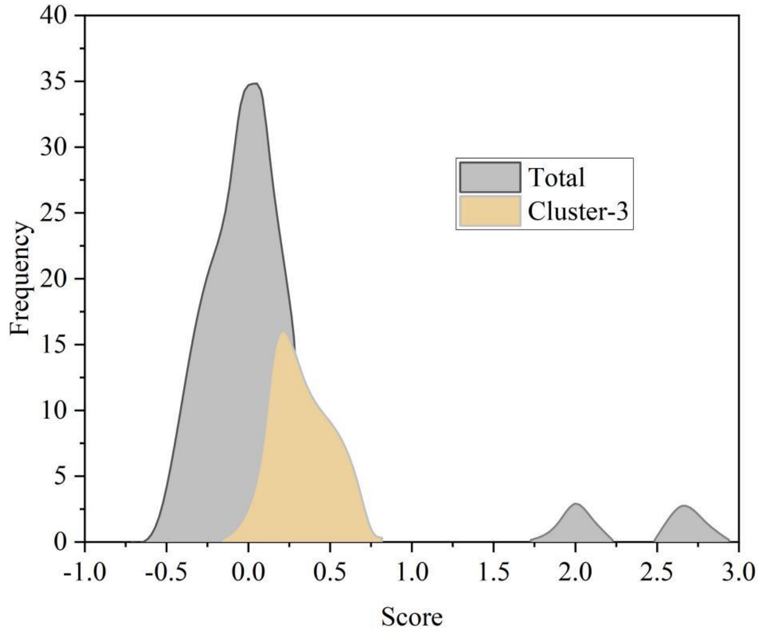


Figure 5: Cluster-3 distribution

By comparing the frequencies and scores of the three clusters horizontally, it is evident that Cluster-1 has the fewest towns and villages, while Cluster-2 has the most, aligning with their respective sizes. The scoring patterns for each cluster also correspond to actual conditions. The specific clustering results are shown in Table 6. As indicated in the table, TX Town and LX Town achieved the highest scores and should be prioritized for logistics network node deployment. TX Town serves as the central town of S County and already houses a logistics distribution center. LX Town, located north of TX Town, is surrounded by numerous developed villages and towns with substantial logistics demand. Its close proximity to the urban area makes it suitable for establishing S County's second logistics distribution center to alleviate the logistics pressure on TX Town. Establishing a logistics distribution center in this location would not only alleviate the current logistics pressure on TX Town but also serve as a focal point to drive development in surrounding villages and towns. This approach would accelerate the construction of S County's logistics network and promote economic growth.

Table 6: K-means clustering result table

Cluster center	Bourg
1	TC town, LX town
2	The town of JF, the town of TS, the town of KH, the town of CH, the town of XL, the new town, the town of SA, the town of JQ, the town of LT, the town of YX, the town of the ZR, the town of WA, the town of new DE
3	the town of L, the town of MJ, the town of XP, the town of E, the stone town, the town of GJ

5 Conclusion

To enhance the operational efficiency of rural e-commerce logistics networks, this paper establishes an innovative rural logistics distribution service model. By integrating factor analysis and k-means clustering models, comprehensive scores are calculated for each township in County S, optimizing the selection of rural e-commerce distribution center locations. Key metrics include GDP, total retail sales of consumer goods, per capita disposable income, and postal service volume. Townships are categorized into three distinct clusters based on these indicators. Comparative analysis of frequency and scores reveals Townships TC and LX as top-ranked clusters. Prioritizing logistics node deployment in these areas will alleviate S County's logistical pressures.

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