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Research Article

The Role of Nonfarm Employment and Service Industries in Enhancing Rural Welfare

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Abstract: This study aimed to explore how incomes from farm and nonfarm activities, the availability of social infrastructure, and proximity to essential service influence family welfare in rural areas. Data were obtained through a sociological survey of 1428 respondents who were heads of households in the Samarkand region villages. Social and economic well-being indices were created using the Factor Analysis model, and the relationship between family heads working in farm or nonfarm industries as well as income sources was examined. Additionally, the Latent Class (Gaussian) analysis model was used to classify households based on proximity to social infrastructure service, categorized as "close," "medium," and "long" distance. The service include food sales, shoe repair, tailoring, restaurants, hair salons, and catering. The results showed that the social and economic welfare of family decreased with each unit increase in the distance from rural homes to social infrastructure service. The relationship was statistically significant at 1% (***, p<.01). In conclusion, this study provided recommendations aimed at improving rural welfare through better access to essential service and the promotion of nonfarm employment initiatives.

Keywords: Factor analysis model; Latent class analysis; Nonfarm activities; Rural population income; Social welfare index

1. Introduction

In agrarian economies, nonfarm activities are increasingly recognized as a cornerstone for rural economic development and welfare improvement, particularly in regions with limited agricultural productivity. Although agriculture remains the primary livelihood for rural households, the low efficiency and vulnerability to external shocks underscore the need for diversified income sources (Haggblade et al., 2010). Nonfarm employment opportunities not only enhance income but also contribute to broader socioeconomic outcomes, such as improved literacy, health, and food security, which are critical for sustaining active and healthy lifestyles (FAO et al., 2014). Studies have consistently demonstrated that nonfarm activities play a crucial role in reducing poverty and fostering economic resilience in rural areas (Neglo et al., 2021; Giannakis et al., 2018; Schultz, 2007; Barrett et al., 2001; Corral and Reardon, 2001).

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The development of nonfarm sectors is particularly transformative in regions where agricultural productivity is constrained by environmental, infrastructural, or institutional barriers. Nonfarm income provides a critical financial buffer for rural family, mitigating risks associated with farming and enabling investment in health, education, and community development (Pishchalkina et al., 2022; Kinghan and Newman, 2017; Reardon et al., 2003; Deininger and Olinto, 2001). These activities can stimulate economic growth and reduce inequality but often lead to shifts in land use patterns and create new challenges for rural governance (Lanjouw and Feder, 2001). In Uzbekistan, where the government has placed significant emphasis on nonfarm activity promotion as a rural development strategy, the socioeconomic benefits remain unevenly distributed due to persistent challenges such as unemployment, limited infrastructure, and declining access to agricultural land (Djanibekov et al., 2012).

The rural areas in Uzbekistan face a complex interplay of economic and infrastructural challenges that necessitate a more nuanced understanding of nonfarm activities and impact on welfare. Nonfarm employment not only diversifies income sources but also strengthens food security and economic stability for rural households (Ning et al., 2023; Ganeshkumar et al., 2020; Reardon et al., 2001). Moreover, land allocation for nonfarm sectors and improved access to social infrastructure have been identified as critical drivers of rural development, enhancing employment opportunities and reducing poverty (Pardaev et al., 2023; Babakholov et al., 2022; Hasanov and Sanaev, 2018; Start, 2001). Studies have further emphasized the importance of proximity to urban centers and the availability of robust rural infrastructure in enabling rural populations to participate effectively in nonfarm activities (Pattayat et al., 2022; De Janvry et al., 2005; Lanjouw and Shariff, 2004).

Proximity to social infrastructure significantly influences household welfare, as family closer to essential service including education, healthcare, and markets demonstrate higher Social Welfare Index (SWI) and Economic Welfare Index (EWI) scores. For instance, access to proximate grocery stores, schools, and health service was associated with improved consumption patterns and reduced economic vulnerability. These results are consistent with broader literature suggesting that investments in rural infrastructure catalyze economic activities and enhance living standards (Fan and Chan-Kang, 2005; Reardon et al., 2003). Furthermore, households engaged in nonfarm employment activities showed higher resilience to economic shocks, validating the role of income diversification as a buffer against agricultural risks (Davis et al., 2010; Barrett et al., 2001).

This study addresses the pressing issue of limited access to socioeconomic service in rural Uzbekistan and the significant implications for family welfare. Despite government interventions, infrastructure deficits and geographical remoteness continue to hinder equitable development. By using advanced analytical models such as Factor Analysis and Latent Class (Gaussian) analysis, this study provides a detailed and context-specific understanding of how spatial disparities in service accessibility affect rural well-being.

The novelty of this study lies in the focused analysis of how proximity to social infrastructure influences the welfare of rural households, using sociological survey data from 1,428 households across 14 districts in the Samarkand region. In contrast to previous investigations which often generalizes the role of nonfarm activities, this study emphasizes the spatial dimension of service accessibility and the direct impact on rural livelihoods. The role of investments in social and economic infrastructure towards nonfarm employment growth was also evaluated to enhance household welfare.

By identifying key factors that influence welfare disparities and proposing actionable policy recommendations, this study contributes to the literature in several ways. First, robust indices for measuring social and economic welfare (SWI and EWI), which can be adapted for similar contexts are introduced. Second, empirical evidence is provided on the critical role of proximity to service in enhancing rural livelihoods. Finally, policy insights that prioritize infrastructure development and targeted nonfarm employment initiatives are offered to address both immediate and long-term challenges in rural welfare enhancement. This study sets the stage for future investigations into innovative approaches to rural development, particularly in the context of digitalization and decentralized service delivery.

2. Methods

The effect of farm and nonfarm activity income on the welfare of rural inhabitants can be examined using a variety of methods and study models. Previous research has used both parametric and non-parametric models to evaluate how population income affects welfare. In this study, the influencing factors were evaluated based on certain functions as a consequence of the employed methodologies. The area of the family farm, unique features of the area, traits of the family, evaluation criteria, consumption costs, and income must all be conceptually evaluated to analyze the factors influencing the population welfare.

The average income per capita or the population total income directly influences socioeconomic indices that measure the welfare of the populace (Gutman et al., 2022). The income from nonfarm activities determines the average income per capita of the rural population. However, the population income from nonfarm activities increases welfare and this has an impact on the growth in farm revenue (Möllers and Buchenrieder, 2011).

Data were collected from a social survey completed by 1428 family (respondents) throughout 14 districts in the Samarkand region in 2022–2023. In the regional districts, there were 852 neighborhood assemblies. The survey was conducted in 97 assemblies, accounting for 11.4% of the total.

Family property was selected as an independent variable because it directly benefits welfare over an extended time in family households. Personal belongings, including car, refrigerator, washing machine, refrigerator (air conditioner), vacuum cleaner, hot water system (Ariston), oven, and remodeled rooms (comfy, according to European standards), as well as the existence of a computer and a water pump, were considered markers of the household social welfare. However, since every home in the social survey had a mobile phone and television, these markers were ignored.

Figure 1 shows the availability of household and utility items in the Samarkand region as a percentage of surveyed households, offering a quantitative perspective on social welfare indicators. Among the variables, refrigerators (Rr) show the highest availability, with over 70% of households owning this essential appliance. Vacuum cleaners (VC) and water pumps (WP) indicate substantial ownership levels, at approximately 65% and 60%, respectively. Washing machines (WM) and comfort of rooms (CR) follow closely, with ownership rates around 50–55%. In contrast, items such as hot water systems (An) and air conditioners (AC) show minimal availability, with less than 30% of households reporting ownership, around 25% and 20%, respectively. Computers (Cr) and cars (PC) also demonstrate limited ownership, both at approximately 35–40%. These figures indicate a significant disparity in the distribution of basic versus non-essential or luxury items.

The data reflects the socioeconomic priorities and constraints of households in the Samarkand region. High availability of refrigerators (70%) and water pumps (60%) emphasizes the focus on fulfilling essential needs such as food preservation and water access. The moderate ownership levels of washing machines (55%) and room comfort (50%) suggest a gradual improvement in living standards for some households. However, the low penetration of air conditioners (20%) and hot water systems (25%) indicate potential barriers, such as affordability or lack of demand driven by climatic or cultural factors. The limited availability of computers (40%) suggests challenges in accessing digital technology, which may hinder educational and professional opportunities.

The family economic welfare was determined by examining the consumer and non-consumer goods and service purchased by household members, such as food, equipment, construction, repair, appliances, utility (gas, electricity, clean drinking water, and other) consumption, health (medical) consumption educational consumption, wedding luxuries, and costs associated with family celebrations, festivals, and ceremonies.

Figure 2 shows a statistical description of household spending across various categories, measured on a scale of 0 to 5. The data indicates that food consumption (Fd) represents the largest expenditure category, with an average score of approximately 3.2, reflecting the significance as a fundamental necessity for households. Education service (En) and expenses on equipment, construction, and repair (ECR) follow with average scores of about 2.5 and 2.4, respectively, indicating moderate spending levels. Spending on weddings, family celebrations, and ceremonies (WCM) averaged around 2.3, indicating the cultural importance of these events.

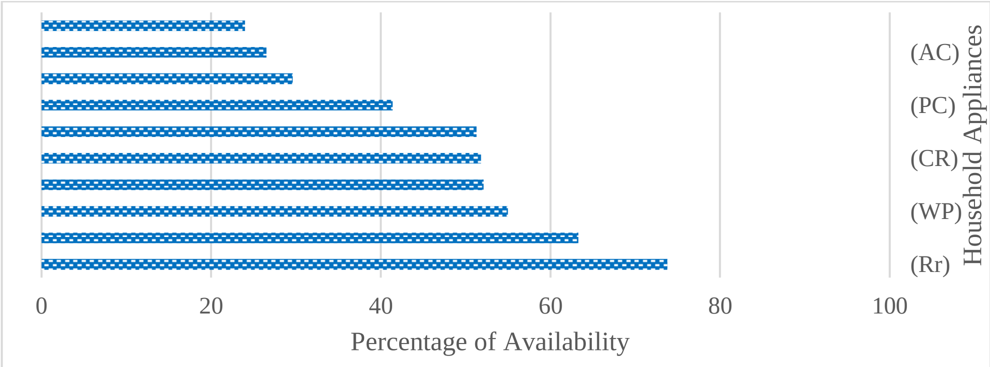


Figure 1 Statistical description of variables representing social welfare. *Refrigerator (Rr); Vacuum cleaner (VC); Water pump (WP); Washing machine (WM); Comfort of rooms (CR); Oven (O); Car (PC); Computer (Cr); Air conditioner (AC); Hot water system (An)*

Other categories, such as household goods and appliances (IA), utilities (UB), and health service (HC), show lower expenditure levels, averaging close to 2.0, suggesting these are relatively lesser priorities or more manageable costs for households. The expenditure distribution provides insights into the socioeconomic priorities and constraints of households. The high spending on food consumption underscores the central role in household budgets, reflecting basic survival needs. Moderate spending on education (2.5) and construction-related costs (2.4) suggest an emphasis on long-term investments in human capital and infrastructure, which are critical for socioeconomic development. Meanwhile, significant spending on weddings and celebrations (2.3) emphasizes the cultural and social obligations that households prioritize, despite economic limitations. The relatively lower spending on utilities, household appliances, and healthcare suggests that either these services are relatively affordable or deprioritized due to financial constraints.

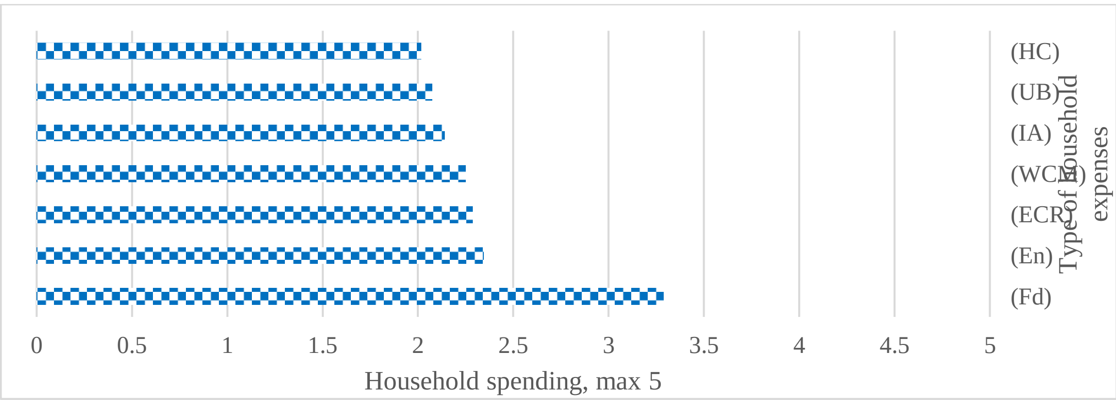


Figure 2 Statistical description of variables representing economic welfare. *Food consumption expenditure (Fd); Education service consumption expenditure (En); Equipment, construction, and repair consumption expenses (ECR); Weddings, family celebrations, events and ceremonies (WCM); Consumer spending on household goods and household appliances (IA); Utilities (gas, electricity, clean drinking water and other) consumption costs (UB); Health (medical) service consumer spending (HC)*

Factors influencing the income from farm and nonfarm activities directly related to the welfare of the population, represented by numerous independent variables as a common feature, led to the creation of new variables using the factor analysis model. An index indication that represented a single common trait across multiple dependent or independent variables was used to express the factor analysis model. However, to use the factor analysis model, three key requirements need to be fulfilled:

1) The Kaiser-Meyer-Olkin Measure, or KMO, is a tool for determining whether a link exists between variables. When KMO is less than 0.50, this suggests that a factor analysis model should be used (Shrestha, 2021);
2) Ch2 Bartlett Test H0: The test evaluates whether the variables show correlation. The alternative hypothesis (H1) shows that the variables do show a correlation. In this instance, the usage of the Factor analysis model will be accepted at 1% when the p-value for the variables used to represent the general characteristic is 0.000 (Cordeiro and Cribari-Neto, 2014);
3) The variables in the correlation matrix are related to one another, and the factor analysis model Det>0.00001 can be used (Acock, 2013);

The general test analysis results show that to create an index indicator from the variables that represent the general characteristic, the aforementioned test conditions must be met. The indices generated from the indicators representing the general variables demonstrate that the factor analysis model perfectly matches the test conditions, based on the cross-sectional survey data collected in 14 districts of the Samarkand region (Table 1).

Table 1 Test results for variables indicating a common characteristic in the factor analysis model

	Indexes	Conditions and test results		
		KMO ≥ 0.50	p = 0.000	Det > 0.00001
1.	SWI	0.826	0.000	0.426
2.	EWI	0.883	0.000	0.111

The general characteristics of the variables that constitute households are stated conditionally in a system of 0–1 value for this index. The characteristic value of the component larger than 1 is approved based on the Kaiser criterion, which explains the variation in the variables.

According to Kaiser's criterion, factors that reflect social and economic well-being must have eigenvalues greater than 1. In this analysis, these factors account for 25.6% of the total variance, and 48.9% of the variance related to social welfare, indicating that the first element represents the variation (Figure 3).

In this analysis, 10 items represent social welfare including an automobile, a refrigerator, a washing machine, an air conditioner, a Hoover, living room repairs and comfort, a computer, and a water pump. It was discovered that one component expressed all of the factors signifying the family economy presence. Moreover, factors that indicate economic welfare include the price of food consumed (Saydullaeva et al., 2023; Ong et al., 2022), equipment, building and maintenance expenses, household products, and appliances. Furthermore, the results showed that one factor could be used to convey the expenses of goods, utilities (gas, electricity, clean drinking water, and others), health (medical) service, education, wedding luxury, family celebrations, ceremonies, and traditions.

The outcomes of the model analysis were determined by identifying the variables in one element. Each variable expressing a common trait should have a coefficient larger than 0.3 (30%). The analysis results indicate that each variable that represents social and economic welfare has a coefficient larger than 30% (Figure 4).

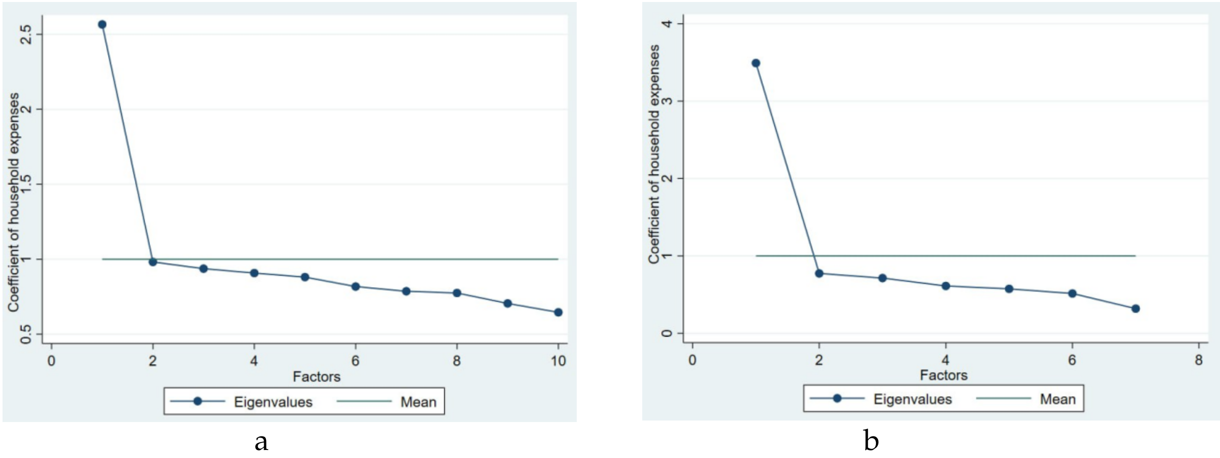


Figure 3 The value of the factors created from variables representing social (Figure a) and economic (Figure b) welfare

Car (PC) accounts for 59.2% of the other variables that represent social welfare, while repair and comfort (CR) accounts for 65.4%. Based on the results, these factors are the primary indicators of social welfare in family households.

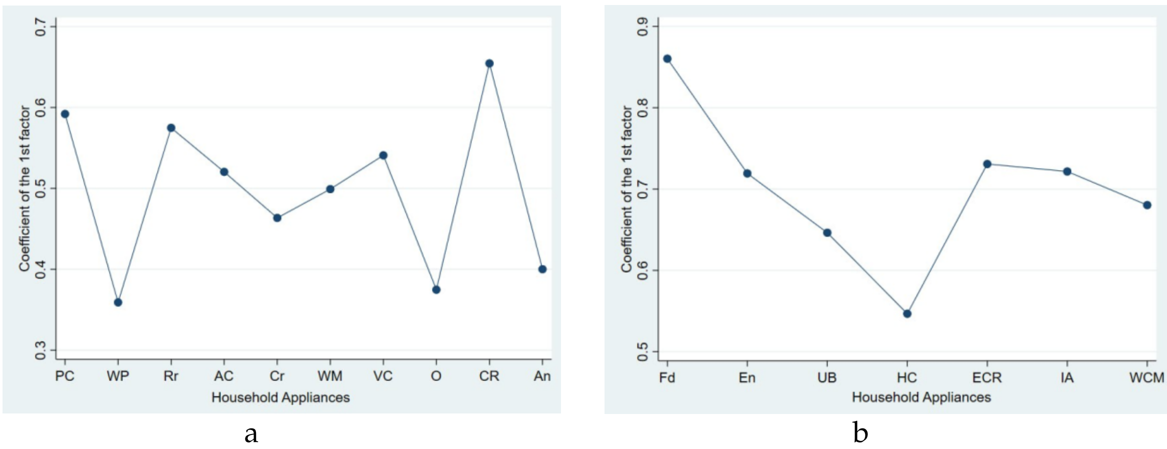


Figure 4 Factor values created from variables representing social (Figure a) and economic (Figure b) welfare

According to the data, 71.9% of the parameters indicating economic welfare are represented by the investment (En) made by the heads of family in the villages for members who are enrolled in preschool, school, or higher education. A significant portion of family consumption expenses goes towards paying for family members education. Food consumption expenditure (Fd) accounts for 86% of the variables indicating economic welfare in family farms. The majority of the population income from both farm and nonfarm activities was used to meet basic needs, such as food. Furthermore, the expenditure on household appliances, building and maintenance of non-food items, as well as other nonfarm activities by family has an impact on the increased social welfare. Specifically, 73.1% of other food and non-food expenses were related to household ECR non-food consumption expenses.

One of the distinguishing characteristics of the factor analysis model (1) is that it establishes the variables range of impact. This is a frequent feature that is connected to the variables influence (heterogeneity). By resolving the multicollinearity issue, it improves the dependability of the acquired results.

The formula of the factor analysis model is expressed as follows (McDonald, 2014):

$$x_i = \sum_{r=1}^{k} l_{ir} f_r + e_i \quad (1)$$

Where: l = interpretation of the remaining variables by the i-th variable in percent, %;
f = general factors;
r = number of factors;
e = standard errors, with a normal distribution;
i = variable, $(i = 1,2\dots,r)$

The factor analysis model explains common variables in an indicator that represents one characteristic (Table 2).

Table 2 Descriptive statistics for newly generated variables derived from the factor analysis model

Variable	Mean	Std.dev	Min	Max
SWI	0.480	0.250	5.54e-17	1
EWI	0.453	0.236	0	1

SWI and **EWI**, expressed between 0 and 1, are indices that reflect the welfare of family in the village, according to the factor analysis results. In general, evaluating the effects of many production or service industries operating simultaneously leads to econometric issues. By generating groups with objective rather than subjective impacts in establishing the range of variables, a latent group analysis model avoids econometric issues. The location of the household, namely the distance from the primary service and social infrastructure facilities was grouped using a latent class (Gaussian) analytic model (Table 3).

Quantitative metrics were used to describe the location of the households from social service institutions. This approach is justified, as every community has at least one educational facility, resulting in minimal variation in household distances to these establishments. However, other social facilities are located far away, either in distant villages, or district centers. Rural inhabitants employment in agricultural pursuits may also be directly impacted by the underdevelopment of service sectors in the communities.

Table 3 Descriptive Analysis for the Latent Class Analysis Model

Variable	Mean	Std.dev	Min	Max
Facilities of social service				
Distance to Preschool	1.705	1.219	0.01	8
Distance to School (DST)	1.254	0.867	0.1	4
The distance to the vocational (technical) educational institution (VET)	4.781	3.292	0.2	33
Distance to Family Polyclinic (FP)	2.172	0.963	0.1	5
Distance to Sports and Health Complex (SHC)	3.945	2.528	0.12	10
Distance to Cinema-Culture Center (CCC)	13.166	6.912	0.1	35
Distance to Library (L)	5.096	4.792	0.1	35
Distance to Further Education Center (FEC)	4.116	2.946	0.1	15
Facilities of service				
Distance to catering service (CS)	3.104	1.752	0.3	8
Distance to Restaurant Service (RS)	2.809	1.582	0.2	7
Distance to Barber and Beauty Salon Service (BBSS)	1.187	0.608	0.1	3
Distance to Shoe Repair Service (ShRS)	2.913	2.143	0.2	9
Distance to Tailoring Service (TS)	1.573	0.813	0.1	3.5
Distance to Grocery Store (GS)	1.051	0.887	0.1	1.9

The Latent class analysis model is expressed by the following formula (2) (Magidson et al., 2020):

$$P[Y_i = y_i | X_i = x_i] = \sum_{c=1}^{K} \gamma_{c_i}(X_i) \prod_{m=1}^{M} \prod_{r_m=1}^{R_m} \rho_{mr_m|c}^{I(y_m=r_m)} \quad (2)$$

Where Y is the response form of the possible vector expression of general respondents;

y - represents the answer sample of a certain respondent;
X - a vector expression of common variables;
x - a vector representation of a given variable
s – groups;
γ – c– the probability of membership in the s-th hidden group;
rm ($\mathrm{rm} = 1, 2, 3, .. \mathrm{rm}$) - option of variables;
$\mathrm{m}(\mathrm{m} = 1, 2, 3, ... \mathrm{M})$ - group index of variables;
$\rho_{\mathrm{mr_m}|\mathrm{c}}^{\mathrm{I}(\mathrm{y_m}=\mathrm{r_m})}$-to the group exponent (m) of the variables with the option probability (rm) conditional on group membership (σ).

The independent variables, which stand for the separations between social infrastructure and service facilities, were grouped using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The distance of family to "social service facilities" was expressed in three categories and a new variable was created from the variables namely preschool and school education, vocational (technical) education, family polyclinic, sports and health complex, film and culture center, library, and science club centers. In other words, it was represented by the close (1), medium (2), and long (3) group indicator characteristic value (Table 4).

A latent class (Gaussian) analysis model classified households based on the distance from grocery (store) service (GSS) to other essential service facilities, including catering service (CS), restaurant service (RX), barber and beauty salon service (BBSS), shoe repair service (ShRS), tailoring service (CTS), and food. Consequently, the characteristic value of the group indicator was categorized into close (1), medium (2), and long (3).

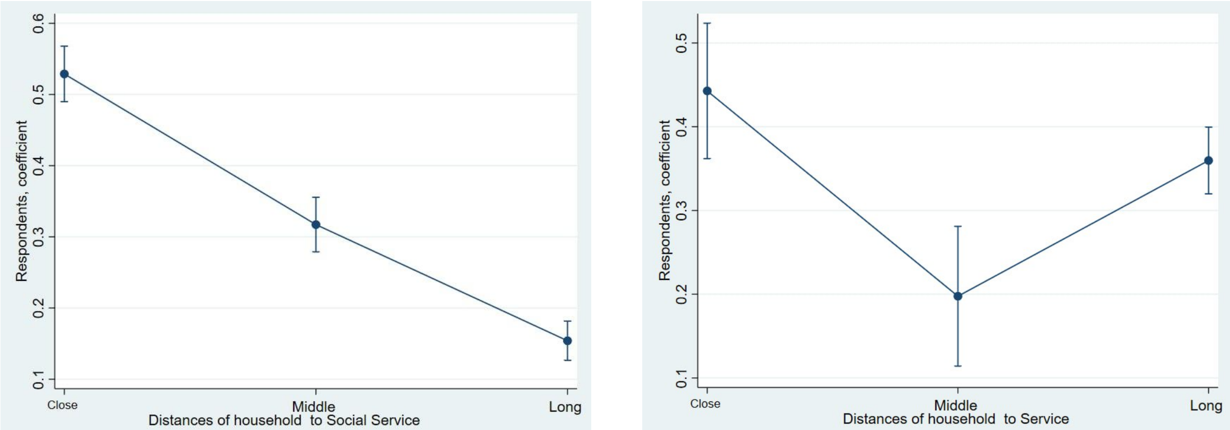
Table 4 Outcomes of the Latent Class Analysis Model AIC and BIC criteria for classifying variables that indicate a common characteristic

	Variable	AIC	BIC	*Entropy*
1.	*Distance to social service objects(Social_LC0029*	51631.9	51716.1	-
		51066.1	51197.7	0.477
		50841.8	51020.8	0.701
		50530.1	50756.5	0.552
2.	*Distance to service objects(Service_LC)*	27075.6	27138.2	-
		26790.9	26890.9	0.667
		26761.6	26898.4	0.681
		26767.9	26941.6	0.560

Entropy was used in clustering to obtain the total number of clusters. In this context, the statistic assessed the degree of variation across the groups and quantified the uncertainty surrounding the value of a random variable. A higher entropy value, closer to 1 indicates more distinct group separations, meaning the variables within each group are clearly classified.

The variables were classified using the Latent Class Analysis Model, and the number of groups representing the smallest indicator in the grouping was determined based on the AIC and BIC criteria. After grouping, the new latent class variable was expressed as a quality indicator (Figure 5).

In the study area, more respondents fall into the "close distance" category when traveling from homes to social service facilities than into the "medium distance" and "long distance" categories combined. In other words, over half of the respondents reside in a region near social assistance facilities. However, there were more respondents overall in the "medium distance" and "long distance" groups than in the "close distance" group. This result may be influenced by the well-being of the populace, as family closeness may lessen the chance that members may engage in nonfarm activities.



a b

Figure 5 Probabilities for Groups Estimated Household Distances to Service and Social Service (Figures a and b) Items

The economic evaluation for the effects of social infrastructure, service sector, and head of family employment in nonfarm activities on the social and economic well-being of family was conducted using the Tobit model (3). When the dependent variable has the tendency of independently reach zero or another limit, the Tobit model can be helpful. This model mathematical statement was stated as follows (Weller et al., 2020).

$$\rho_i^* = \beta_0 + \sum_{j=1}^{i} \beta_j x_{ij} + \varepsilon_i \quad (3)$$
$$\rho_i = \rho_i^* \qquad 0 \le p_i^* \le 1$$
$$\rho_i = 0 \qquad p_i^* < 0$$
$$\rho_i = 1 \qquad p_i^* > 1$$

Here, ρ_i^* - unplanned variables;
ρ_i – dependent variable;
x_{ij} – independent variable;
β_0 – unchangeable;
β_j – correlation vector coefficient;
ε_i – $\varepsilon_i \sim N(0, \sigma 2)$

An economic assessment of the variables influencing the social and economic welfare of rural people was conducted using this model and the "STATA-17" software program.

3. Results and Discussion

The nonfarm and service sectors significantly improve the welfare of rural populations by diversifying income sources, generating employment, and reducing poverty. These sectors provide supplementary income and reduce dependence on agriculture, mitigating risks such as crop failure and price volatility. Other functions include creating jobs, particularly for women and youth while fostering skill development and promoting gender equality. Access to service such as healthcare, education, and financial institutions enhances living standards and reduces poverty. Furthermore, these sectors strengthen rural-urban linkages by stimulating local economies, promoting infrastructure development, and reducing migration pressures. By offering economic stability and resilience, nonfarm and service activities contribute to sustainable development and empower marginalized groups, ultimately improving the quality of life in rural communities.

The SWI and the EWI are critical tools for assessing and improving social infrastructure service in rural areas by providing a comprehensive evaluation of living standards and economic conditions. These indices can guide policymakers in prioritizing investments and interventions. For instance, in Uzbekistan, a village with a low SWI indicating poor access to education, healthcare, and basic utilities, might prompt the government to allocate resources for constructing schools, clinics, or water supply systems. Similarly, a low EWI reflecting limited income opportunities or poor employment rates can inform the development of programs aimed at fostering entrepreneurship or supporting agricultural cooperatives. As a practical example, in a rural district of Samarkand region, these indices could identify a need for expanded microfinance service and vocational training to enhance economic resilience, while simultaneously addressing gaps in social service such as maternal healthcare. This integrated approach ensures that economic and social challenges are tackled holistically, fostering sustainable development.

The SWI and EWI can be classified based on components, typically grouped into standard dimensions or indicators. These classifications allow for a comprehensive and systematic evaluation of welfare.

The average SWI for a household with a head who engages in nonfarm activities is 0.602. Similarly, a family head whose primary source of income is farm activities has a higher SWI than the overall index by 0.268, according to the analysis results in Figure 6.

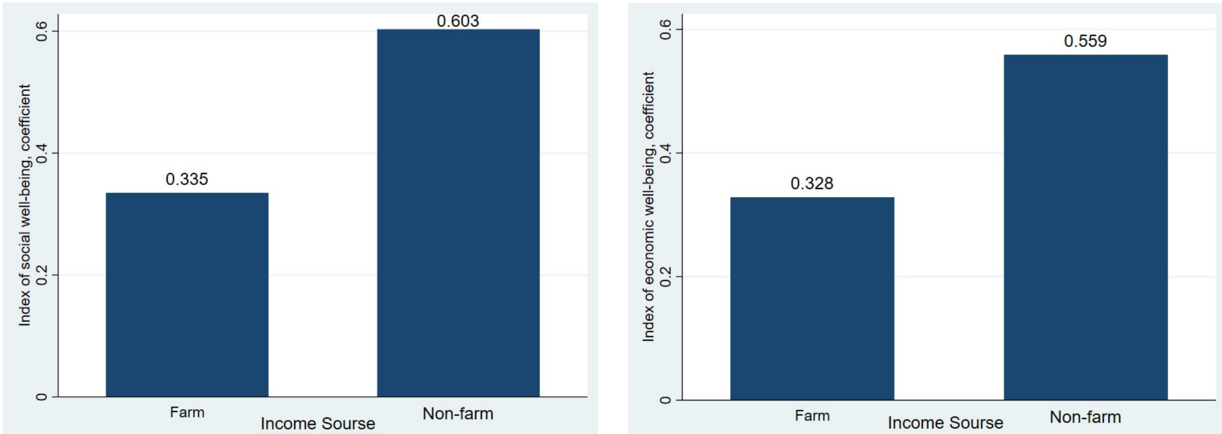


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Figure 6 The contribution of farm and nonfarm income to the rural population's social and EWIes (a and b)

The average EWI is equal to a 0.559 coefficient in households where the family head engages in nonfarm activities as the primary source of income. In other cases, where the family head engages in farming activities, the average EWI is 0.231.

The percentage of food consumption expenses rises due to the village population rising income. The villagers will not be able to provide for family food needs when there is no change in the makeup of population expenditures, which implies a decline in the share of food products consumed.

Figure 7 shows the analysis results, indicating that the family "SWI" and "EWI" indicators were influenced by the distance between social infrastructure service and households. The use of social infrastructure service by family members enhances consumption when available in the village. The "SWI" and "EWI" coefficients of 0.623 and 0.581 were obtained by the fact that family members reside in the village close to social infrastructure service. In most cases, the village social infrastructure ensures that everyone lives comfortably and has a job. The public will be more inclined to buy or use assets that symbolize social welfare when income is stable. The results emphasize the importance of enhancing village social infrastructure service to improve family well-being.

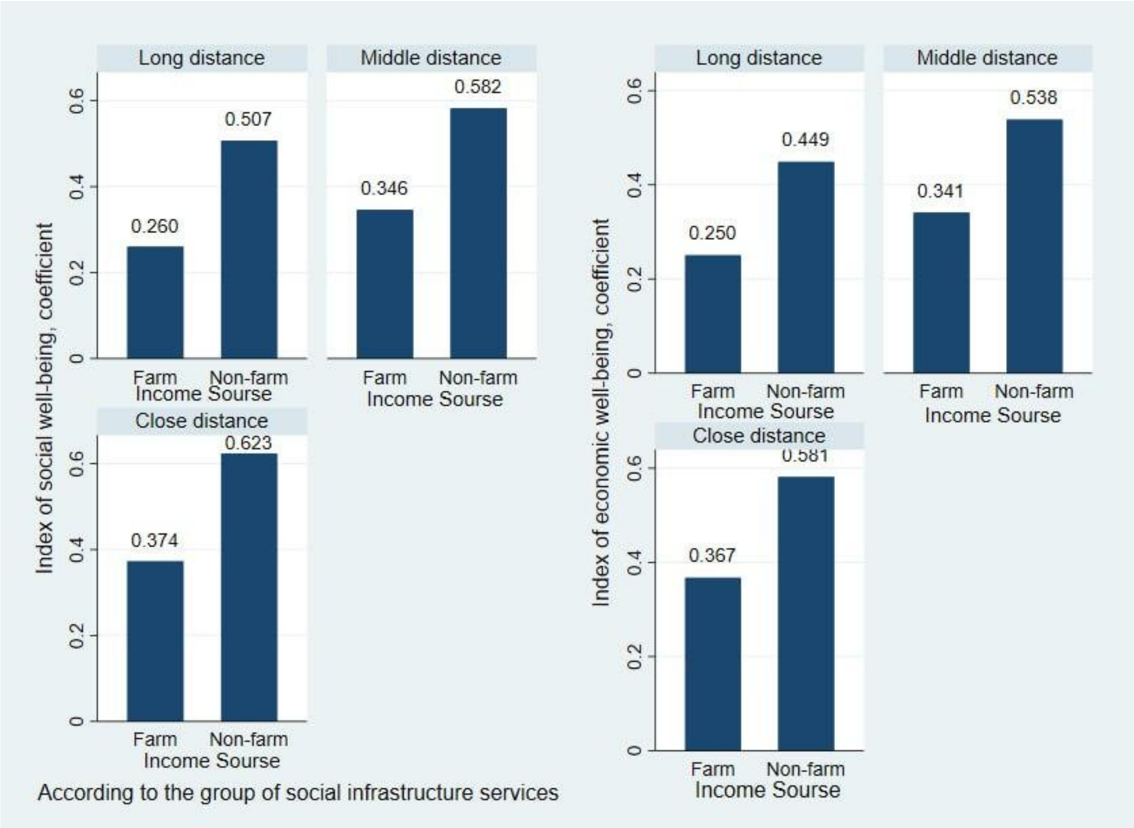

Figure 7 A statistical examination of the service provided by social infrastructure for the social and economic well-being of villagers' populations

The "SWI" and "EWI" ratio was 0.260:0.25 when the family is mostly supported by farm income and is situated in the hamlet remote from the center of social infrastructure service. In this instance, the social and economic welfare is impacted by the fact that the family resides far from the village social infrastructure service.

The SWI of 0.623 and the EWI of 0.581 for the Samarkand region suggest moderate levels of social and economic well-being, with room for improvement. These values, as standardized indices ranging from 0 to 1, allow for direct comparison with other regions or similar countries, serving as benchmarks for evaluating social infrastructure service and development priorities.

For instance, when a neighboring region such as Bukhara shows a SWI of 0.700 and an EWI of 0.650, it indicates relatively better access to healthcare, education, and economic opportunities, perhaps due to more robust social programs or better connectivity to markets. On the other hand, Karakalpakstan, with hypothetical indices of 0.500 (SWI) and 0.450 (EWI), might reflect significant deficits in social infrastructure, including healthcare facilities or economic diversification, often worsened by environmental challenges such as water scarcity.

Comparison to similar countries considered rural regions in Kazakhstan or Kyrgyzstan. A rural district in Kazakhstan might score 0.650 (SWI) and 0.620 (EWI), reflecting slightly higher economic resilience due to natural resource exploitation. Conversely, a rural area in Kyrgyzstan could score 0.600 (SWI) and 0.550 (EWI), emphasizing comparable struggles with income inequality and access to quality healthcare.

These indices are particularly valuable for identifying disparities and setting development goals. For example, in Samarkand, a focused improvement in areas such as healthcare access or vocational training could potentially raise both indices, while comparison with better-performing regions or countries helps prioritize interventions namely expanding education programs or upgrading transport infrastructure. Therefore, the SWI and EWI are effective tools for comparative analysis and decision-making, ensuring targeted investments in social infrastructure service where most needed.

The results imply that the opening of grocery stores, shoe repair, beauty salons, restaurants, public catering, and other businesses in the villages will help to increase the number of jobs available to the people. Rural inhabitants' employment in turn has an impact on family income. In other words, family that live "close" to service facilities have a higher SWI than those living "long distance," by nearly 0.1 coefficients (Figure 8).

The growth of the service sectors in villages is impacted by the fact that family heads work primarily in nonfarm or rural areas. However, population affluence has a direct impact on service sector growth.

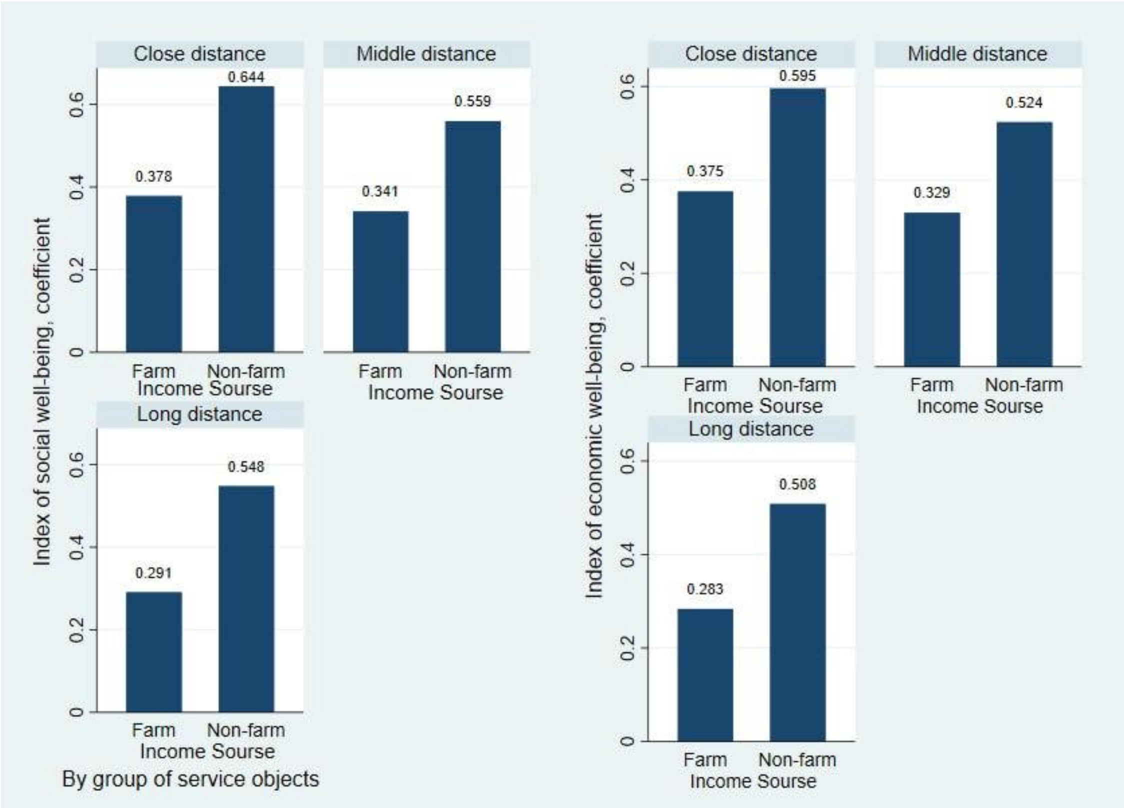

Figure 8 A statistical examination of the service provided to the social and economic well-being of villagers' populations

The SWI is 0.378 for the head of family engaged in farm activities, and 0.643 for those participating in nonfarm activities, and have service facilities near family farms. On the other hand, the SWI of family engaged in farming activities is 0.088 coefficient higher at 0.290 than those participating in farming activities at "close distance." At this stage, the SWI of household heads engaged in "long distance" and "close distance" nonfarm activities differ by a coefficient of 0.096.

The social welfare of rural populations and the service sectors may not be significantly correlated, but the analysis results indicate that these sectors have an impact. The food store that operates in the village may have an impact on indicators that show the economic well-being of the residents, specifically the consumption of food items. Simultaneously, the nonfarm activities offer family who lack financial resources the chance to consume goods or service for a set amount of time. Family financial well-being is impacted by the structure of the service sectors in the neighborhoods. Specifically, family residing in "close distance" and engaged in nonfarm activities experience higher economic welfare than those residing in "long distance" service industries, with a coefficient of 0.087. This illustrates the effect of volunteer work on the financial security of farming households. The economic evaluation of factors influencing the "SWI" and the "EWI" further demonstrates the significance of proximity to social and economic service areas in shaping family welfare (Table 5).

The SWI and EWI of family decreased by 0.02 and 0.019, respectively, when service areas from rural households were distributed into one unit, such as from "close distance" to "medium distance" or "medium distance" to "long distance." This effect is statistically significant at 1% level (***, p<.01). Furthermore, the creation of social service zones in rural areas, particularly those adjacent to family farms, benefits the socioeconomic well-being of farmers and vice versa. The analysis results indicate that household's economic welfare was more impacted by the proximity of social service locations than social welfare.

Table 5 The stable model analysis's outcome in evaluating the economic factors influencing rural inhabitants welfare

Influence factors	Social welfare	Economic welfare
	Coef. (St.Err.) & Sig.	
Service_LC	-0.020 (0.004)***	-0.019 (0.005)***
Social_LC	-0.019 (0.006)***	-0.026 (0.006)***
Non_farm	0.106 (0.009)***	0.082 (0.009)***
Education	0.223 (0.007)***	0.205 (0.007)***
Male	0.059 (0.011)***	0.055 (0.011)***
Age	0.024 (0.006)***	0.029 (0.006)***
Age2	0.0002 (0.00006)***	0.0003 (0.00006)***
Constant	-0.494	-0.628
var(e	0.022	0.023
Mean dependent var	0.480	0.454
Pseudo r-squared	16.118	-16.743
Chi-square	1511.701	1275.138
Akaike crit. (AIC)	-1399.909	-1333.298
SD dependent var	0.250	0.236
Number of obs	1428	1425
Prob > chi2	0.000	0.000
Bayesian crit. (BIC)	-1352.532	-1285.940

**** p<.01, ** p<.05, * p<.1*

The use of social service is directly influenced by family members income, and the distance from service restricts the frequency of visits. Consequently, family members limit expenditures for the present time or do not use social service, which has an adverse effect on financial welfare. Employment of family heads in nonfarm activities improved the social and financial well-being of households, raising the SWI and EWI by 0.106 and 0.082, respectively. However, food product consumption expenditures are greater than other consumption and non-consumption costs which raise the family expenses. This expenditure pattern also raises the likelihood of investing in appliances, household goods, building and repair consumption, and equipment that contributes to the social welfare of family members. In other words, family whose heads of the household work in nonfarm pursuits aimed at ensuring the well-being of family members or a profitable existence.

The results show that improving the social and economic welfare of a family depends more on the education of the leaders than members. For every unit increase in the education level of household head, SWI and EWI rise by 0.223, a statistically significant effect at 1 % effect (*** p<.01). Although the age of the family heads showed a positive correlation with the rise in welfare, the effect declined at older ages.

The EWI results are in line with established patterns in rural household income and expenditure dynamics, as evidenced by existing literature. Barrett et al. (2001) and Davis et al. (2010) reported the transformative impact of nonfarm income sources on rural households economic stability. Diversification into nonfarm activities reduces exposure to agricultural risks and provides more consistent income streams, thereby improving overall well-being. These results are consistent with the observation showing that households engaged in nonfarm activities have higher average EWI values compared to those reliant on farming activities, underscoring the role of economic diversification in enhancing resilience.

The reported trend of increasing food consumption expenses with rising income supports Engel's Law, stating that although the proportion of income spent on food decreases as income grows, absolute food expenditure tends to increase. This is consistent with the broader implications of household expenditure shifts reported by (Clements and Si, 2018), who emphasize the necessity of sustained rural economic growth and structural transformation in expenditure patterns to ensure food security and sustainable livelihoods. The results contribute to the discourse on rural development by emphasizing the critical interplay between income diversification, consumption dynamics, and economic resilience, offering a nuanced perspective on improving household welfare through targeted policy interventions and support for nonfarm economic activities.

The influence of social infrastructure on family welfare is closely related to the established evidence in the literature on rural development and infrastructure role in enhancing household well-being. Fan and Chan-Kang (2005) emphasized that investments in rural social infrastructure significantly contribute to improving economic productivity and family incomes, underscoring the positive externalities of proximity to the service. Similarly, Jalan and Ravallion (2003) demonstrated that access to essential social service, including education and healthcare, enhances household consumption capacity and reduces poverty levels, underscoring the critical link between infrastructure accessibility and welfare.

The "SWI" and "EWI" coefficients namely 0.623 and 0.581 for family near social infrastructure, compared to 0.260:0.25 for those further away reflect disparities in household welfare directly linked to proximity, mirroring patterns observed in the literature. Proximity to infrastructure facilitates greater income diversification and consumption opportunities, while households located farther away are often limited to less stable income sources, such as farming, and face heightened economic vulnerabilities due to restricted access to resources and service.

The stable income and accessible social infrastructure motivate family to invest in social welfare assets. Similarly, Canning and Bennathan (2000) stated that improved infrastructure indirectly enhances household incomes by reducing transaction costs and increasing productivity. This study reinforces the critical need for policies aimed at expanding and improving rural social infrastructure, as it plays a crucial role in bridging welfare disparities and fostering equitable economic development.

The relationship between family income sources and service sector growth in rural areas is consistent with broader studies on rural economic development. For example, Reardon et al. (2007) and Davis et al. (2010) showed that nonfarm income sources contribute significantly to household welfare and stimulate local service sectors. The results showing higher SWI coefficients for households engaged in nonfarm activities, reinforce the idea that income diversification fosters service sector growth. Moreover, proximity to service facilities further supports these outcomes, showcasing the combined importance of economic activity and infrastructure in rural development.

The results are in line with recent literature emphasizing the significant role of family head employment and social service access in rural household welfare. Davis et al. (2010) and Reardon et al. (2007) reported that nonfarm employment enhances household well-being by increasing income, enabling better access to service, and facilitating investments in household goods, similar to the positive effects observed in this study on the SWI and EWI. Additionally, the importance of education in improving family welfare, as shown by the significant coefficient for education, is supported by broader studies. For example, Beegle et al., (2006) explained how education influences economic outcomes and social welfare in rural areas. These results further confirm that nonfarm activities and education significantly contribute to enhancing social and financial stability in rural households.

4. Conclusions

In conclusion, this study underscores the critical role of the service industry in enhancing the social and economic well-being of rural populations, with particular emphasis on the importance of nonfarm employment for household welfare. Using a latent group model, the analysis classified rural households based on proximity to social infrastructure service into "close," "medium," and "long" distance categories. The results showed that increased distance from social care institutions negatively affects family social and economic welfare, indicating that proximity to facilities is a significant factor in improving household well-being. Specifically, households located within the "close distance" category experience better social and economic outcomes. This suggests that reducing the remoteness of villages from essential service facilities can significantly enhance rural residents' quality of life. However, future studies should explore the role of technological advancements, such as digital service, in bridging the gap between remote rural areas and critical infrastructure. Further investigation is needed to identify the most effective policy interventions and analyze the long-term sustainability of nonfarm employment initiatives in rural contexts. The government should prioritize the development of agriculture and nonfarm businesses through targeted state programs to foster employment opportunities and sustain economic growth in rural areas while addressing these evolving challenges.

5. Perspective for Further Study

The results emphasize the transformative potential of proximity to social infrastructure service and the role of nonfarm employment in improving rural household welfare. Future studies can extend this work by examining how digitalization and new technologies mitigate the challenges posed by physical remoteness. Investigating the potential of e-commerce, telemedicine, and online education in enhancing rural access to critical service could provide innovative solutions to geographic constraints. Additionally, longitudinal studies exploring the sustainability and economic impact of nonfarm employment initiatives across diverse rural contexts in Uzbekistan and other developing regions would deepen understanding of these interventions.

6. Challenges for Further Study

Key challenges include addressing disparities in digital infrastructure and ensuring equitable access to new technologies in rural areas. Investigating the scalability of digital solutions while accounting for variations in digital literacy, economic resources, and cultural acceptance poses methodological and implementation difficulties. Moreover, evaluating the long-term viability of state-led nonfarm employment programs requires comprehensive data on economic and social impacts over time. Finally, the influence of climate change and environmental degradation on rural service accessibility and agricultural sustainability adds another layer of complexity that future studies must address.

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Author Contributions

Shukrullo Muratov led the conceptualization of the research framework and designed the survey instrument for data collection in the Samarkand region. He was responsible for defining the research objectives, coordinating fieldwork activities across 14 districts, and developing the empirical model to assess the relationship between nonfarm employment, infrastructure proximity, and rural welfare. He also contributed significantly to drafting the introduction, methods, and conclusion sections of the manuscript.

Ekaterina Burova served as the project's scientific supervisor, overseeing the methodological rigor of the study. She provided guidance on the application of the Factor Analysis and Latent Class (Gaussian) models, ensuring compliance with international statistical standards. She contributed extensively to refining the analytical framework and provided critical revisions to the manuscript, particularly in the results interpretation and discussion sections.

Svetlana Suloeva supported the statistical modeling and validation process, with a particular focus on entropy, AIC/BIC criteria, and econometric testing using the Tobit model. She played a key role in reviewing the literature on rural service accessibility and contributed to the visualization and interpretation of the SWI and EWI indices. Additionally, she assisted in aligning the manuscript with the journal's formatting and academic requirements.

Shavkat Hasanov contributed to the development of the theoretical background related to nonfarm income and welfare, drawing on both local and international literature. He led the geospatial analysis of household proximity to service infrastructure and contributed to the interpretation of statistical outputs from the latent class analysis. He also co-authored the section on rural policy implications and comparative regional analysis.

Khusniddin Pardaev was involved in the design and implementation of the data processing strategy. He contributed to coding and cleaning the survey dataset, calculated the household-level SWI and EWI indicators, and conducted regression diagnostics in STATA. He also contributed to writing the results and discussion sections, especially regarding the economic effects of infrastructure proximity and employment status.

Bokhodir Isroilov provided theoretical insights into service sector development and its integration into rural livelihoods. He contributed to drafting the literature review, particularly on economic diversification, infrastructure investment, and rural development. He also provided critical feedback on the final manuscript draft and contributed to harmonizing the academic tone and narrative flow of the paper.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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