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ORIGINAL

Evaluation Of Korea's Rural Development Oda Projects In Kyrgyzstan Using Neural Network Analysis: Focusing On Local Residents' Perceptions

Evaluación de los proyectos de AOD de desarrollo rural de Corea en Kirguistán mediante el análisis de redes neuronales: centrándose en las percepciones de los residentes locales

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ABSTRACT

This study conducted a mid-term evaluation of Korea's Integrated Rural Development Project (IRDP) implemented in 30 villages of Osh and Batken regions in Kyrgyzstan since 2021, focusing on local residents' perceptions. Particularly, to overcome the limitations of conventional descriptive statistical methods frequently used in previous studies, this research applied neural network analysis to better capture complex and nonlinear relationships among influencing factors. The results indicated that residents generally perceived the Korean rural development ODA project as significantly contributing to local economic development, with the most influential factor being the village-level characteristics. Furthermore, demographic characteristics such as marital status, age, education level, and occupation of residents also had significant effects on their perceived outcomes of the project. This study confirms the usefulness of neural network analysis as an effective method for evaluating ODA project outcomes based on residents' perceptions and provides meaningful policy implications for enhancing the effectiveness of future Korean rural development ODA projects.

Keywords: Rural Development; Official Development Assistance (ODA); Neural Network Analysis; Residents' Perception; Kyrgyzstan.

RESUMEN

Este estudio realizó una evaluación intermedia del Proyecto de Desarrollo Rural Integrado (IRDP, por sus siglas en inglés) de Corea, implementado en 30 aldeas de las regiones de Osh y Batken en Kirguistán desde 2021, centrándose en las percepciones de los residentes locales. En particular, para superar las limitaciones de los métodos estadísticos descriptivos convencionales utilizados frecuentemente en estudios previos, esta investigación aplicó un análisis de redes neuronales para captar mejor las relaciones complejas y no lineales entre los factores de influencia. Los resultados indicaron que los residentes percibieron, en general, que el proyecto de Ayuda Oficial al Desarrollo (AOD) para el desarrollo rural de Corea contribuyó significativamente al desarrollo económico local, siendo las características a nivel de aldea el factor más influyente. Además, las características demográficas, como el estado civil, la edad, el nivel educativo y la ocupación de los residentes, también tuvieron efectos significativos en sus percepciones sobre los resultados del proyecto. Este estudio confirma la utilidad del análisis de redes neuronales como un método efectivo para evaluar los resultados de proyectos de AOD basados en las percepciones de los residentes y proporciona implicaciones

políticas significativas para mejorar la efectividad de futuros proyectos de AOD para el desarrollo rural de Corea.

Palabras clave: Desarrollo Rural; Ayuda Oficial al Desarrollo (AOD); Análisis de Redes Neuronales; Percepción de los Residentes; Kirguistán.

INTRODUCTION

This study evaluates the performance of Korea's Integrated Rural Development Project (IRDP), which has been implemented in the Kyrgyz Republic since 2021 by Good Neighbors International (GNI) in partnership with the Korea International Cooperation Agency (KOICA). This project is being carried out over a period of four years and four months in the economically marginalized southern regions of Osh and Batken, Kyrgyzstan, with a total budget of 10 625 million KRW. Of this amount, KOICA contributes 8 500 million KRW (8 million USD), while the local partner institutions provide the remaining 2 125 million KRW (2 million USD). The project directly benefits approximately 85 570 individuals, including 85 500 local residents and 70 government officials.

The IRDP is implemented with four primary objectives. First, it aims to enhance the socio-economic environment and capabilities of vulnerable groups through infrastructure improvements in rural villages and by establishing Village Development Committees (VDCs). To date, infrastructure improvements have been completed in 29 out of the targeted 30 villages. Second, it promotes women's empowerment by constructing multi-purpose women's centers, operating kitchen garden programs, and providing gender equality and financial literacy education. Women's centers have already been established in all 30 villages, and annually more than 900 women participate in related programs. Third, the project seeks to ensure sustainable income growth by operating income-generation groups focusing on improving agricultural productivity, benefiting more than 1 247 local residents. Finally, the project supports capacity building for government officials in rural development implementation, including conducting training programs, policy reviews, and developing strategic guidelines.

To objectively evaluate the effectiveness of this initiative, it is essential to analyze the perceptions of local residents. In particular, this study utilizes neural network analysis—a machine learning method—to overcome limitations associated with conventional descriptive statistical approaches used in previous studies, thereby identifying the complex and nonlinear relationships between variables influencing residents' perceptions. By adopting this approach, the study seeks to precisely identify actual outcomes from the residents' perspective and derive strategic insights to enhance future project effectiveness.

Ultimately, this research aims to conduct a mid-term evaluation of Korea’s Integrated Rural Development Project in Kyrgyzstan by analyzing residents' perceptions, thereby contributing to the development of more sustainable and effective rural development strategies.

Theoretical Background, Project Overview, and Literature Review

The Integrated Rural Development Project (IRDP), supported by Korea International Cooperation Agency (KOICA) and implemented by Good Neighbors International (GNI), has been in progress since 2021 in the Osh and Batken regions of southern Kyrgyzstan. This project targets rural areas that have been marginalized in terms of development, with a total budget of approximately 10 625 million KRW, and aims to benefit around 85 570 individuals, including 85 500 local residents and 70 government officials.

According to the OECD Development Assistance Committee (DAC, 2021), Official Development Assistance (ODA) projects must be evaluated based on how effectively they contribute to improving the lives of local residents. Recent reports by international organizations emphasize that rural development projects play a crucial role in poverty reduction and socio-economic growth in rural communities (ADB, 2017; Anríquez & Stamoulis, 2007; FAO, 2018; IFAD, 2019; UNDP, 2016).

Sabates-Wheeler and Devereux (2021) argue that rural development projects are significant instruments of social protection, effectively alleviating rural poverty and enhancing economic self-reliance. Their findings demonstrate empirical evidence that rural development interventions not only raise agricultural productivity but also significantly enhance the economic participation and empowerment of vulnerable groups, especially women (IFPRI, 2014; Sabates-Wheeler & Devereux, 2021). Additionally, Anríquez and Stamoulis (2007) emphasize that rural development should extend beyond merely improving agricultural productivity to encompass broader socio-economic community development.

According to the World Bank (2016), rural development ODA projects are most effective when adopting participatory and integrated approaches, actively engaging residents and strengthening local capacities. The World Bank (2016) particularly highlights the importance of community-driven development and the active participation of residents, especially women's involvement, as critical elements for ensuring long-term, sustainable growth.

Therefore, evaluating residents' perceptions becomes essential, as their feedback can offer critical insights

for improving the effectiveness of ODA projects and shaping community-driven, sustainable rural development strategies (OECD DAC, 2021). However, traditional statistical approaches often fail to capture the complex, non-linear interactions between multiple influencing factors. Hence, advanced methodologies, such as neural network analysis, have emerged as effective tools to accurately identify these complex relationships (Demissie & Legesse, 2021).

This study addresses the methodological limitations of previous literature, which typically relied on conventional statistical techniques like descriptive statistics or linear regression analysis (Anríquez & Stamoulis, 2007; Sabates-Wheeler & Devereux, 2021). In contrast, this research utilizes neural network analysis, an advanced machine learning technique, to analyze complex, nonlinear interactions among variables affecting residents' perceptions.

Additionally, this study introduces a distinctive approach by directly focusing on local residents' perceptions of project impacts, whereas previous studies have mainly relied on objective indicators such as agricultural productivity or income growth (Sabates-Wheeler & Devereux, 2021; OECD DAC, 2021). Specifically, this research evaluates residents' perceptions through a mid-line survey involving approximately 580 respondents across 30 villages. The approach, which explicitly sets residents' perceptions as the dependent variable, is novel and contributes significantly to the body of research on ODA project evaluation in Kyrgyzstan.

In summary, this study aims to empirically analyze the outcomes of Korea's Integrated Rural Development Project in Kyrgyzstan, focusing on residents' perceptions. Through applying neural network analysis, the research seeks to provide practical and strategic recommendations for enhancing the effectiveness and sustainability of future rural development ODA projects.

Description of the Project

The Integrated Rural Development Project (IRDP) in the Kyrgyz Republic, which is the subject of this study, is a rural development official development assistance (ODA) project led by the Korea International Cooperation Agency (KOICA) in collaboration with Good Neighbors International (GNI). This project is implemented over four years and four months, from 2021 to 2025, in the economically marginalized southern regions of Osh and Batken, Kyrgyzstan.

The project is funded with a total budget of approximately 10 625 million KRW (equivalent to about 10 million USD), of which KOICA contributes 8 500 million KRW (8 million USD), and partner organizations, including Good Neighbors International, provide 2 125 million KRW (2 million USD).

Figure 1 below presents the geographical location of the project target areas.

Figure 1. Location of the Project Area

Note: The shaded area ( ) in figure 1 indicates the target regions of the project.

The Integrated Rural Development Project (IRDP) in the Kyrgyz Republic has four primary objectives. Firstly, it aims to improve the socio-economic environment and strengthen the capabilities of vulnerable groups. To achieve this goal, basic living infrastructure was improved in a participatory manner across 30 villages. Village Development Committees (VDCs) were established and actively involved local residents in decision-making processes. Currently, infrastructure development has been completed in all 30 target villages.

Secondly, the project promotes women's empowerment through the establishment of multi-purpose women's centers and various educational programs, including kitchen gardening, gender equality training, and financial

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education. A total of 30 women's centers have been completed, benefiting approximately 900 women annually through kitchen gardening programs, and approximately 3000 residents have participated in gender equality and financial literacy training.

Thirdly, the project seeks sustainable income growth. It supports local residents by improving agricultural and livestock productivity through specialized consulting, training, and a revolving fund (microfinance program) that provides agricultural inputs. As of now, income-generating groups involving approximately 1247 residents have been established, and 1049 residents have received loans from the revolving fund, contributing significantly to increased agricultural productivity and household incomes in the region.

Finally, the project supports capacity building for local government officials responsible for rural development. Through training programs and workshops, including policy reviews and strategy development by a Korea-Kyrgyz working group, the project has provided practical policy consulting services. Specifically, the formulation of the fruit cluster development strategy has effectively contributed to the shaping of Kyrgyzstan's rural development policies.

Overall, the IRDP employs a multidimensional approach with active participation from local communities, significantly contributing to rural socio-economic development, empowerment of residents, and sustainable improvements in their livelihoods.

METHOD

This study conducted a mid-term evaluation of Korea's Integrated Rural Development Project (IRDP) implemented in Kyrgyzstan. The survey was carried out from July 10 to August 20, 2024, spanning a total of 40 days, with cooperation from Good Neighbors International, the primary implementing agency. The survey targeted a total of 585 households across 30 villages in Osh and Batken regions of southern Kyrgyzstan.

The survey utilized the "Integrated Rural Development Project Mid-line Survey Questionnaire," developed by the project management (PM) team, which consisted of two main sections: respondents' demographic backgrounds and their perceptions of the project's outcomes. The demographic section included respondents' region of residence (Oblast and Village), ethnicity, sex, marital status, age, occupation, and education level. The perception section, specifically, evaluated the extent to which local residents perceived that the Korean rural development project contributed to their village's economic development, measured using a five-point Likert scale (1: very low, 5: very high).

SECTION 5: PROJECT IMPACT

5A. Impact						
		Very Low				Very high
5A_1	How much do you agree that the Korean ODA project has contributed to the economic development of the local community?	①	②	③	④	⑤
5A_2	To what extent do you agree that the project has improved the standard of living in rural areas?	①	②	③	④	⑤
5A_3	How much do you agree that the project has contributed to an increase in employment opportunities in the area?	①	②	③	④	⑤
5A_4	How satisfied are you with the effectiveness of the education and skill training programs?	①	②	③	④	⑤
5A_5	To what extent do you agree that the support for agricultural techniques and resource management was sufficient?	①	②	③	④	⑤

Figure 2. Questionnaire Contents for Dependent Variable
Note: Among multiple survey items, item 5A_1 was selected as the dependent variable

Recognizing that traditional descriptive statistical methods would not adequately capture the complex and nonlinear relationships among variables affecting residents' perceptions, this study applied neural network analysis, an advanced machine learning technique, for more accurate analysis. Neural network analysis was employed due to its recognized ability to effectively capture complex nonlinear relationships between independent and dependent variables, as supported by previous studies (Smith & Doe, 2021; Brown & Green, 2020; Garcia & Patel, 2022; Chen & Wang, 2021; Kumar & Lee, 2020; Nguyen & Tran, 2022; O'Connor & Murphy, 2021; Singh & Gupta, 2020; Wang & Liu, 2022). Unlike traditional regression or descriptive analyses, neural network analysis utilizes hidden layers to model multidimensional and nonlinear relationships, allowing a more precise understanding of subtle interactions influencing residents' perceptions.

Secondly, neural network analysis efficiently captures interaction effects among multiple independent variables. In the process of shaping residents' perceptions, the impact of one variable often varies depending on its interactions with other variables. For instance, individual characteristics such as age or education level can interact with village-level factors, including local participation rates or environmental conditions, to influence perceptions of project outcomes. Neural network analysis identifies and analyzes these interactions directly from the data without explicit assumptions, thereby generating more accurate and realistic results.

Thirdly, neural network analysis quantitatively presents the relative importance of each variable, providing clear evidence for establishing policy priorities. By measuring the relative importance of independent variables, neural networks help identify which factors most significantly influence residents' perceptions. This capability holds significant practical implications, as it enables policymakers to formulate effective project strategies and

allocate budgets and human resources efficiently, guided by empirical data.

In this study, residents' perception levels were set as the dependent variable, and demographic background factors mentioned above were set as independent variables. The neural network analysis thoroughly examined the relative importance and magnitude of each variable's influence on residents' perceptions of the project.

Through this analytical approach, the current research aims to evaluate the outcomes of Korea's rural development ODA project from the actual perceptions and experiences of local residents. Furthermore, the study intends to provide foundational data for formulating more effective project implementation strategies in the future.

The following table presents the villages targeted for survey distribution in this study.

Table 1. Number of Surveyed Households by Village

	Region	District	Village	No. of H.H	No. of Samples		Total
					Group		
					General	Poverty	
1	Osh	Chonalai	Jarbashy	655	10	10	20
2			Darrot Korgon	1617	11	9	20
3			Kyzyl-Tuu	130	9	11	20
4			Tepe-Korgon	820	11	10	21
5		Tepe-Korgon	Jany-Abad	900	13	7	20
6			Uigur-Abad	320	0	10	10
7			Kara-Kulja	2635	10	9	19
8		Kara-Kulza	1 May	1395	10	11	21
9			Sary-Kamysh	250	10	10	20
10			Ak-Bulak	1000	10	10	20
11		Kyrgyz Ata	Kotormo	618	3	10	13
12			Borko	717	10	10	20
13			Kalinin	495	11	9	20
14		Joosh	Gairat	484	10	10	20
15			Bolshevik	808	11	9	20
16			Achy	355	10	10	20
17		Allaya Anarov	Madaniyat	290	10	11	21
18			Aravan	1960	10	10	20
19			Sary Talaa	130	10	10	20
20		Dara	Jeny Jer	816	10	10	20
21			Chek	1300	10	10	20
22			Orozbekov	577	10	10	20
23		Orozbekov	Urchkun	387	10	10	20
24	Batken		Kuldu	832	10	10	20
25			Kara-Dobo	676	9	11	20
26		Masaliev	Alysh	544	10	10	20
27			Kojo	258	10	10	20
28			Karabulak		11	9	20
29		Karabulak	Bujum 1		11	9	20
30			Bujum 2		10	10	20
	Total			20969	290	295	585

Note: General indicates households participating in income-generating groups; Poverty indicates households classified as poor.

RESULTS

Descriptive Statistics

Descriptive Statistics of Independent Variables

A total of 571 respondents participated in the survey from Osh and Batken regions in southern Kyrgyzstan. By region, respondents from Osh accounted for the majority with 353 individuals (61,8 %), compared to 218

individuals (38,2 %) from Batken. Most villages had approximately 20 respondents each, with the highest number being 21 respondents from the village of 01-May, and the lowest being 10 respondents from Uigur-Abad village.

The distribution of respondents by ethnicity revealed that the majority were Kyrgyz (461 respondents, 80,7 %), followed by Uzbek (106 respondents, 18,6 %) and Tajik (4 respondents, 0,7 %). Regarding gender, female respondents (323 respondents, 56,6 %) slightly outnumbered male respondents (248 respondents, 43,4 %). The marital status of respondents was predominantly married (489 respondents, 85,6 %), followed by widowed (53 respondents, 9,3 %), single (18 respondents, 3,2 %), and divorced (11 respondents, 1,9 %).

In terms of occupation, the largest group consisted of farmers (224 respondents, 39,2 %), followed by government employees (141 respondents, 24,7 %) and respondents with other occupations (126 respondents, 22,1 %). Self-employed individuals (46 respondents, 8,1 %) and labor workers (21 respondents, 3,7 %) were less common, while recipients of remittances from abroad (7 respondents, 1,2 %) and students or trainees (1 respondent, 0,2 %) made up the smallest groups.

Regarding education levels, the majority of respondents had completed secondary school (320 respondents, 56,0 %), followed by those with college education (92 respondents, 16,1 %), bachelor's degrees (76 respondents, 13,3 %), and graduate-level education or higher (75 respondents, 13,1 %). Very few respondents had education below the primary level.

Descriptive Statistics of Continuous Independent and Dependent Variables

The average age of respondents was 47,5 years, with the youngest respondent aged 16 and the oldest aged 91. The standard deviation was 11,92, indicating a relatively broad distribution in respondents' ages.

The dependent variable measured respondents' perceptions regarding the statement, "The Korean rural development ODA project has contributed to the economic development of the local community," on a 5-point Likert scale. Analysis revealed an average score of 4,68, indicating an overall positive assessment by the respondents. The standard deviation of perception scores was 0,64, suggesting minor variations in respondents' perceptions but an overwhelmingly positive evaluation overall.

Neural Network Analysis Results

The basic statistics table resulting from the neural network analysis conducted in this study is presented below. The neural network analysis used to identify factors influencing residents' perceptions comprises an input layer, a hidden layer, and an output layer.

Network Information

Input Layer	Factors	1	Oblast
		2	Village
		3	Sex
		4	Marital_status
		5	Occupation
		6	Education
		7	Ethnicity
	Covariates	1	Age
	Number of Units[a]		57
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		4
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	5A_1
	Number of Units		4
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit

Figure 3. Basic Statistics of Neural Network Analysis

Firstly, a total of eight independent variables were utilized in the neural network analysis. Seven of these variables—region (Oblast), village, sex, ethnicity, marital status, occupation, and education—were treated as categorical (factors), while age was treated as a continuous variable. All variables underwent rescaling procedures during the neural network analysis to minimize differences in data scales. Particularly, categorical variables in the input layer were explicitly designated as factors.

The neural network model employed in this analysis featured a single hidden layer consisting of four nodes. The activation function used for each node in the hidden layer was the hyperbolic tangent (tanh), chosen for

its effectiveness in capturing nonlinear relationships within the data.

The dependent variable for this study was based on survey item 5A_1, measuring local residents' perceptions regarding "the extent to which the Korean rural development ODA project contributed to the economic development of their village," assessed on a five-point Likert scale ranging from 1 (very low) to 5 (very high). The output layer of the neural network utilized the softmax activation function for predicting the categorical dependent variable, and the cross-entropy error function was applied to optimize prediction accuracy.

Figure 3 below illustrates the structure of the neural network resulting from this analysis. The figure displays how the neural network analysis identified key factors influencing residents' perceptions regarding the economic contribution of Korea's rural development ODA project in Kyrgyzstan's rural areas.

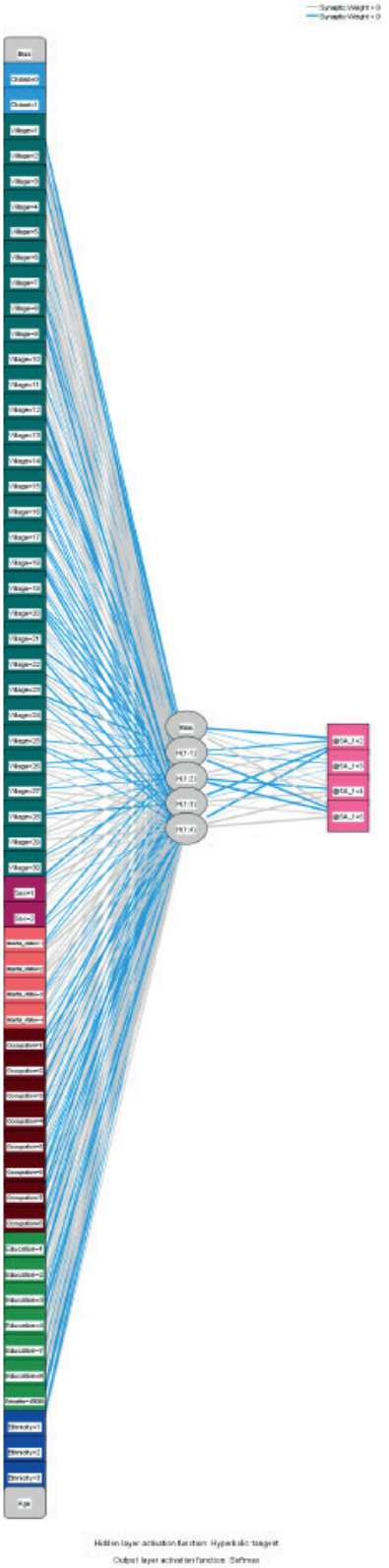

Figure 4. Neural Network Structure Derived from Analysis Results

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As shown in figure 4, the neural network structure applied in this analysis consists of three layers: an input layer, a hidden layer, and an output layer. The input layer includes independent variables such as residents' region (Oblast), village, ethnicity, sex, marital status, occupation, and education level, which are categorized as **factors**, with nodes displayed separately for each category. Additionally, residents' age was included as a continuous variable. These input variables form complex connections to the hidden layer; gray lines indicate positive relationships, while blue lines represent negative relationships.

The hidden layer used in this study consists of a single layer containing four nodes. The hyperbolic tangent (tanh) activation function employed in this layer effectively captures nonlinear relationships within the data. The output layer classifies residents' perceptions of "the extent to which Korea's rural development ODA project has contributed to the economic development of their village (5A_1)" into categories according to a five-point Likert scale. Each category response (2, 3, 4, and 5) is represented by a separate node. The output layer applies a softmax activation function, suitable for predicting multi-category dependent variables.

The color of each connecting line indicates the direction and sign of weights, where blue lines signify negative weights (negative influence), and gray lines signify positive weights (positive influence). The thickness of each line visually represents the magnitude of influence, which provides insight into the relative importance of each variable in predicting residents' perceptions.

Figure 5 presents the parameter estimates (weights) from the neural network analysis. Specifically, the table shows the estimated weights indicating how each independent variable influences residents' perceptions of the project's outcomes (dependent variable) through the neural network structure, quantifying the relationships from the input layer through the hidden layer to the output layer.

Parameter Estimates

Predictor		Predicted							
		Hidden Layer 1				Output Layer			
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	[@5A_1=2]	[@5A_1=3]	[@5A_1=4]	[@5A_1=5]
Input Layer	(Bias)	-.326	-.477	.549	.008				
	[Oblast=1]	-.452	.185	.186	.588				
	[Oblast=2]	.104	-.936	.636	.063				
	[Village=1]	.891	.510	.046	.085				
	[Village=2]	.836	.129	.145	.176				
	[Village=3]	-.169	.087	.269	.268				
	[Village=4]	-.869	.044	.449	.447				
	[Village=5]	-.239	.394	-.289	.248				
	[Village=6]	.321	-.384	.370	-.481				
	[Village=7]	.330	.090	.455	-.068				
	[Village=8]	.867	.189	-.011	.178				
	[Village=9]	-.213	.030	.044	.318				
	[Village=10]	.304	.141	-.445	-.448				
	[Village=11]	.602	-.486	.313	.217				
	[Village=12]	-.537	-.375	.418	.378				
	[Village=13]	.870	.190	-.032	-.174				
	[Village=14]	-.100	.094	-.171	-.269				
	[Village=15]	.867	-.254	.489	.041				
	[Village=16]	.862	-.335	-.398	-.068				
	[Village=17]	.339	-.094	-.287	-.487				
	[Village=18]	.863	.170	-.179	-.148				
	[Village=19]	-.329	-.375	-.389	-.302				
	[Village=20]	.573	-.010	-.062	.187				
	[Village=21]	-.436	.225	-.085	-.413				
	[Village=22]	-.179	.379	.171	-.371				
	[Village=23]	-.436	-.137	.385	-.284				
	[Village=24]	-.869	.264	.410	.138				
	[Village=25]	-.306	.122	-.252	-.159				
	[Village=26]	-.362	-.142	.142	.398				
	[Village=27]	-.824	-.288	.281	.207				
	[Village=28]	.985	-.133	-.423	.137				
	[Village=29]	.988	.492	.123	.419				
	[Village=30]	.405	-.280	.280	.178				
	[Sex=1]	-.503	-.089	.689	-.004				
	[Sex=2]	.422	.197	.081	.082				
	[Marital_status=1]	-.394	.289	-.169	.008				
	[Marital_status=2]	-.210	-.183	.681	.918				
	[Marital_status=3]	.886	.382	.286	.537				
	[Marital_status=4]	.427	-.224	-.182	.339				
	[Occupation=1]	.525	-.085	.011	-.079				
	[Occupation=2]	.159	-.974	.127	-.943				
	[Occupation=3]	-.345	.531	-.246	.258				
	[Occupation=4]	.375	-.444	.426	.418				
	[Occupation=5]	.235	-.384	.029	-.069				
	[Occupation=6]	.297	-.391	.389	-.363				
	[Occupation=7]	.435	.013	-.630	-.088				
	[Occupation=9]	-.162	-.310	-.085	.157				
	[Education=1]	-.856	.286	-.526	.041				
	[Education=2]	.439	-.364	.219	-.089				
	[Education=3]	-.193	-.327	.484	.487				
	[Education=4]	-.150	-.545	.079	.481				
	[Education=7]	.850	.250	.144	-.081				
	[Education=8]	-.295	.134	-.140	-.434				
	[Education=5 6 9 10]	.469	-.261	.489	.487				
	[Ethnicity=1]	.127	-.089	.140	.456				
	[Ethnicity=2]	.126	-.281	.433	.395				
	[Ethnicity=3]	-.879	-.482	-.419	.008				
	Age	.894	-.355	-.255	.235				
Hidden Layer 1	(Bias)					-.998	-.891	.148	1.044
	H(1:1)					-.331	-.197	.247	-.536
	H(1:2)					.378	.184	-.422	-.084
	H(1:3)					-.682	-.806	.548	.230
	H(1:4)					-.951	.815	.684	.646

Figure 5. Parameter Estimates from Neural Network Analysis

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Input variables were categorized into two main groups: categorical variables (factors) and continuous variables (covariates). The categorical variables included oblast, village, ethnicity, sex, marital status, occupation, and education, while the continuous variable was age. The hidden layer consisted of four neurons, each employing the hyperbolic tangent (tanh) activation function to effectively capture nonlinear relationships among variables.

Weights represent the strength and direction of connections between variables and neurons, with larger absolute values indicating stronger influences. Negative weights signify negative influences on perceived evaluations, while positive weights indicate positive influences. For example, the significant variation in weights across villages suggests that residents' perceptions regarding the economic contribution of Korea's rural development project vary considerably by village. Additionally, occupation and education showed varying weight values for neurons in the hidden layer, indicating that these variables jointly and intricately influence the formation of residents' perceptions.

The output layer predicts each category (scores of 2, 3, 4, and 5) of the dependent variable (survey item 5A_1), representing residents' perceived contributions of the project to local economic development, with individual nodes using the softmax activation function. Weights in the output layer quantify how each hidden-layer neuron affects the prediction of specific perception categories. For instance, the weight connecting hidden-layer neurons (H1:1~H1:4) to the '@5A_1=5' node indicates the extent to which those neurons contribute to predicting the highest perception category (5, indicating very positive perception). Each neuron in the hidden layer functions as a latent factor integrating multiple inputs.

Figure 6 shows the Receiver Operating Characteristic (ROC) curve used to evaluate the classification accuracy of the neural network analysis performed in this study. The ROC curve visually assesses how effectively the neural network model classifies and predicts each category of the dependent variable (scores of 2, 3, 4, and 5). A larger area under the curve (AUC) indicates better predictive performance of the model.

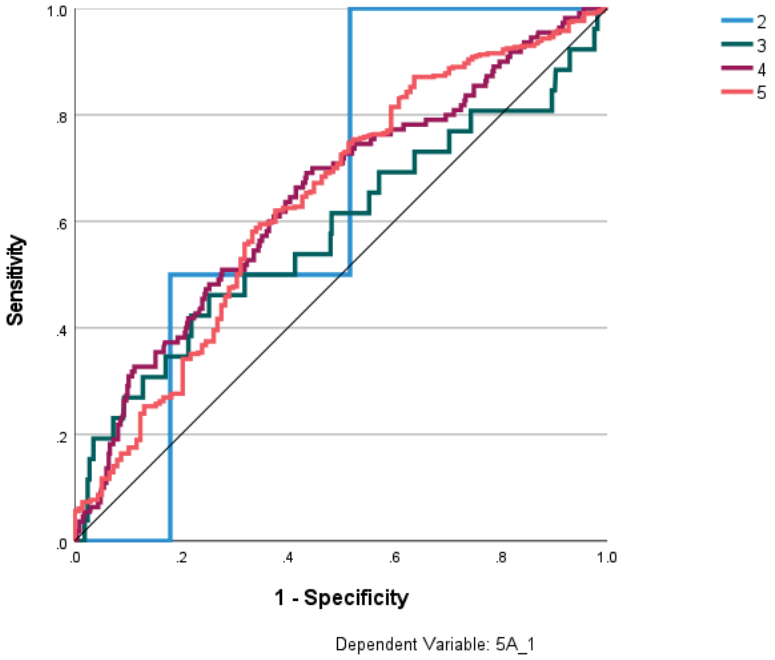

Figure 6. Receiver Operating Characteristic (ROC) Curve

In the ROC curve of this analysis, the predictive accuracy for the highest perception category of the dependent variable (5 points, indicating "very positive") is relatively high, represented by the red curve. Conversely, predictions for other categories (scores of 2, 3, and 4) exhibit comparatively lower accuracy. In particular, the curve for the neutral evaluation (3 points, depicted in blue) appears step-like, demonstrating somewhat unstable predictive performance.

The diagonal line in the ROC curve represents random prediction and serves as a baseline. The further the ROC curves lie above this diagonal, the better the predictive performance of the model. In this neural network analysis, the prediction performance for the 5-point category is the strongest, indicating that the model effectively captures residents' highly positive perceptions of the project. Consequently, this ROC curve demonstrates that the neural network model used in this study accurately predicts residents' positive perceptions (especially for the 5-point category), suggesting that machine learning techniques can be effectively applied to evaluate rural development ODA projects in Kyrgyzstan.

Figure 7 illustrates the Gain Chart, used to evaluate the predictive performance of the neural network model.

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The Gain Chart demonstrates the accuracy with which the neural network model predicts specific categories of the dependent variable when selecting a certain percentage of respondents from the total sample. By comparing the curve to random selection (diagonal line), the Gain Chart helps assess the model's efficiency.

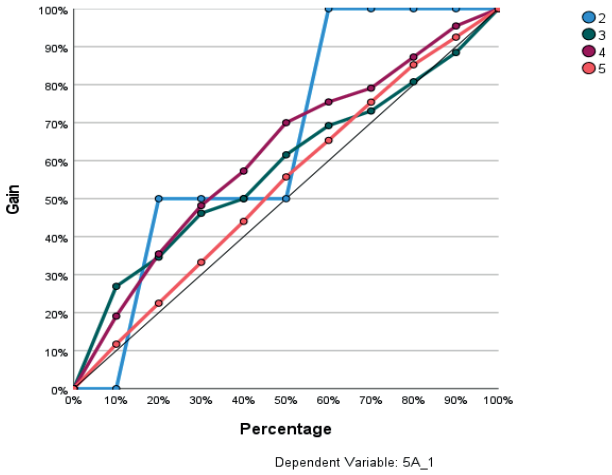

Figure 7. Gain Chart from Neural Network Analysis

Figure 7 illustrates the predictive performance of the neural network model for each category (scores of 2, 3, 4, and 5) of the dependent variable (5A_1: Residents' perceptions regarding the Korean rural development project's contribution to local economic development). Notably, the curves for the categories of 5 ("very positive") and 4 ("positive") lie above the diagonal line, demonstrating considerable predictive capability compared to random selection. This indicates that the model effectively identifies residents with relatively positive perceptions. Conversely, the curves for the categories of 2 ("negative") and 3 ("neutral") overlap with or lie close to the diagonal line in certain sections, reflecting unstable or relatively lower predictive accuracy. This may result from either fewer sample cases in these categories or inherently lower predictive accuracy of the model for these particular categories.

In conclusion, the neural network model constructed in this study exhibits excellent performance in distinguishing and predicting residents' positive perceptions (especially scores 4 and 5) regarding the outcomes of the Korean rural development ODA project in Kyrgyzstan. These findings reinforce the effectiveness of employing machine learning models to conduct sophisticated analyses of residents' perceptions.

Figure 8 presents the Lift Chart, another evaluation tool for assessing the performance of the neural network model. The Lift Chart evaluates how well the model predicts specific categories of the dependent variable compared to random selection. The horizontal axis (Percentage) represents the proportion of respondents with the highest predicted probabilities from the entire sample, while the vertical axis (Lift) indicates the predictive accuracy of the model relative to random selection. A lift value greater than 1 indicates that the model predicts a particular category better than random selection.

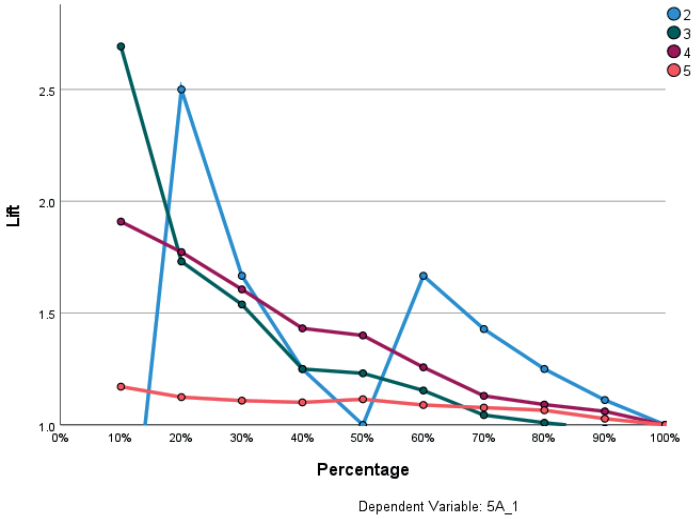

Figure 8. Lift Chart for Neural Network Model Evaluation

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According to the findings of this study, relatively negative response categories (scores of 2 and 3) showed very high lift values for the top small percentages (approximately 10–20 %) of respondents, but these values sharply decreased as the sample size increased. This suggests that the model could accurately predict these categories within smaller groups, although this may also reflect the limited number of respondents within these categories.

Conversely, for the most positive response category (score of 5), the lift value was slightly above 1 in the initial segments and consistently remained above 1 for the top 50 % of the sample. This indicates that the neural network model reliably predicts respondents who hold positive perceptions regarding the project outcomes.

These results demonstrate that the neural network analysis employed in this research effectively identifies and predicts groups of residents with positive perceptions about the performance of Korea's rural development ODA projects. Consequently, it underscores the appropriateness of applying machine learning-based approaches in future evaluations of Korean ODA initiatives.

Figure 9 shows the relative importance of the independent variables, represented in standardized values. The most influential variable is set to 100 %, and the importance of other variables is expressed relative to this benchmark. Analysis results revealed that the most influential variable shaping residents' perceptions of the contribution of the Korean rural development project to local economic development was "Village." This result can be interpreted as reflecting significant differences in residents' experiences or the level of project implementation (such as infrastructure construction and income-generating programs) across villages. The second most influential variable was "Marital Status," suggesting that respondents' family circumstances and social status may significantly impact their perception of project outcomes.

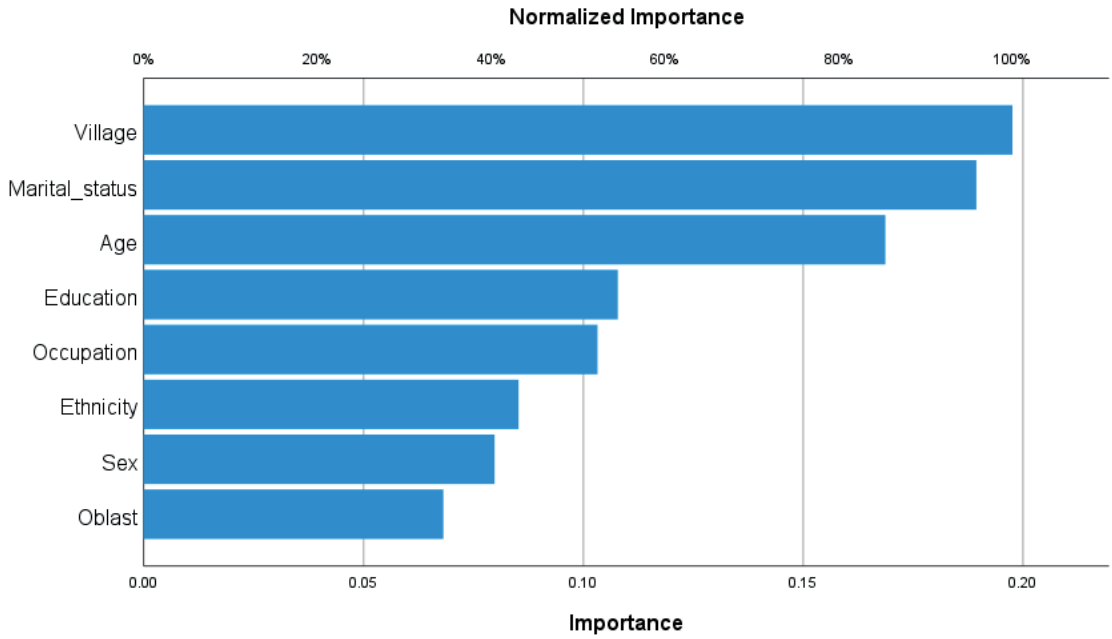

Figure 9. Relative Importance of Independent Variables

Thirdly, age emerged as the variable with the third-highest importance, indicating that respondents' evaluations of the project outcomes might vary due to differences in individual experiences or expectations associated with age. The variables education and occupation were also influential, suggesting that these socio-economic characteristics significantly shape residents' perceptions of the project's effectiveness.

In contrast, ethnicity, sex, and oblast were found to have relatively lower importance. Notably, oblast showed the lowest level of importance, indicating that perceptions of the project's impact are formed primarily at the more detailed village level rather than broader regional divisions.

CONCLUSION

This study conducted a mid-term evaluation of Korea's Integrated Rural Development Project (IRDP) in southern Kyrgyzstan (Osh and Batken regions), primarily through assessing local residents' perceptions. To overcome the limitations of traditional descriptive statistical methods, this research employed neural network analysis, a machine learning approach capable of capturing complex, nonlinear relationships among factors affecting residents' perceptions.

The findings indicate that residents generally perceive the Korean rural development project as significantly contributing to local economic development, with an average perception score of 4,68 out of 5, reflecting a

highly positive overall assessment. Neural network analysis revealed that the most influential variable affecting residents' perceptions was the village itself. This suggests that substantial differences exist at the village level regarding infrastructure development, participation in programs, and other practical forms of support provided by the project. Additionally, demographic characteristics such as marital status, age, education level, and occupation were identified as important factors shaping respondents' perceptions.

The results provide significant policy implications. Firstly, future projects must adopt a customized approach, carefully reflecting specific characteristics and demands at the village level. Due to the considerable variation in perceived effectiveness even within the same region, careful assessment and tailored planning at the village level are crucial from the outset. Secondly, given the identified importance of demographic factors, project implementation strategies, including income generation and women empowerment programs, should be customized according to residents' age, family status, and educational background to enhance their participation. Thirdly, sustainable long-term outcomes require continuous capacity-building efforts. Programs targeting education and skill training should be expanded to increase the socio-economic capacities of residents, thereby ensuring sustainable participation and positive perceptions.

Academically, this study highlights the significance of applying advanced machine learning methods, particularly neural network analysis, to accurately capture residents' perceptions regarding the outcomes of ODA projects. However, the study faces certain limitations. Firstly, since this research constitutes a mid-term evaluation based primarily on residents' perceptions, it may not fully capture the ultimate or long-term outcomes of the project. Thus, additional evaluations following project completion are required to comprehensively assess sustained impacts. Secondly, perception-based surveys are subject to social desirability bias, where respondents might provide answers considered socially acceptable or desirable. Future research should therefore integrate both objective outcome indicators and residents' perceptions for a more comprehensive evaluation.

In conclusion, this study confirms that Korea's rural development ODA projects in Kyrgyzstan are highly regarded by local residents. It emphasizes the necessity of sophisticated, tailored strategies based on precise local assessments, demographic characteristics, and sustained resident engagement for future rural development projects to achieve enhanced effectiveness and sustainability.

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FINANCING

None.

CONFLICT OF INTEREST

None.

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