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Spatial Analysis of Household Financial Distress in Penajam Paser Utara Regency Amid the Dynamics of Nusantara Capital City (IKN) Development

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ABSTRACT

This study analyzes factors influencing household financial distress in Sepaku District, Penajam Paser Utara Regency, and spatial relationships among areas affected by IKN development. Primary data from questionnaires were analyzed using Ordinary Least Squares (OLS), K-Nearest Neighbor (KNN), Moran's I, Local Indicators of Spatial Association (LISA), Lagrange Multiplier (LM), Spatial Autoregressive Model (SAR), and Spatial Error Model (SEM). Results indicate positive spatial autocorrelation and clustering. SAR was selected as the model based on the lowest AIC of 3040.495. Household income (X_1) and road accessibility (X_6) negatively and significantly affect household financial distress (Y), while educational level of household head (X_2), occupation of household head (X_3), number of household dependents (X_4), and travel time to the nearest economic center (X_5) are not significant.

INTRODUCTION

Regional development brings changes in economic activities, infrastructure conditions, and patterns of household livelihoods. The expansion of investment and the development of new economic centers are expected to create employment opportunities and improve household welfare. However, the benefits of development may not be distributed equally because households have different capacities in accessing economic resources, education, employment opportunities, and supporting facilities. Therefore, assessing development outcomes requires an understanding of household socioeconomic conditions in addition to regional economic indicators (Todaro & Smith, 2020).

Household financial distress has become an important issue in understanding economic vulnerability at the household level. Financial distress refers to a condition where households experience difficulties in fulfilling basic needs, maintaining financial stability, and managing financial risks under uncertain conditions. Previous studies indicate that household financial distress is influenced by several socioeconomic characteristics, including income, education, employment status, and household conditions (Fernández-López, Álvarez-Espiño, Rey-Ares, & Castro-González, 2024); (Noerhidajati , Purwoko, Werdaningtyas, Kamil, & Dartanto, 2021); (Saraçoğlu , 2026). In addition, external pressures, such as income shocks and increasing

expenditure burdens, may reduce households' ability to maintain financial stability (He & Zhou, 2022). Household financial management capability also plays an important role in strengthening resilience against economic uncertainty (Liu, Fan, Li, & Yue, 2024)

Although household characteristics are important factors, financial distress may also be influenced by the characteristics of the surrounding area. Differences in transportation infrastructure, accessibility, and proximity to economic centers affect households' opportunities to access employment, markets, and income sources (Takada, Morikawa, Idei, & Kato, 2021); (Wiegand, Koomen, Pradhan, & Edmonds, 2023); (Kebede, 2024). Households living in areas with limited accessibility may face greater challenges in participating in economic activities. These conditions suggest that financial distress is not only an individual household issue but may also have a spatial dimension, where neighboring areas may experience related economic conditions (Gao, 2024); (Hanin, Meilandra, Debataraja, & Pertiwi, 2024).

The spatial dimension of household financial distress becomes particularly relevant in regions experiencing rapid development transformation. The development of Indonesia's Nusantara Capital City (IKN) has created substantial changes in East Kalimantan through infrastructure development, investment expansion, land-use changes, and the emergence of new economic activities. Sepaku District, North Penajam Paser Regency, represents an important area in this transformation because it has been designated as the core development area of IKN. While the development process provides new economic opportunities, households with limited education, skills, and income sources may experience difficulties in adapting to these changes. As a result, the economic impacts of development may vary among households within the same region.

Understanding these variations requires an analytical approach that considers spatial relationships. Conventional regression methods, particularly Ordinary Least Squares (OLS), are widely used to examine relationships between socioeconomic variables. However, OLS assumes that observations are independent and that the relationship between variables remains constant across locations. These assumptions may limit the analysis of regional phenomena because socioeconomic conditions in one area may be associated with conditions in surrounding areas (Comber, et al., 2023). Spatial regression methods provide an alternative approach by incorporating spatial dependence and geographical variation into the analysis (Chakraborty, et al., 2022).

Several spatial approaches have been applied to analyze regional socioeconomic issues. The Spatial Autoregressive Model (SAR) is used to capture spatial interactions through neighboring observations, while the Spatial Error Model (SEM) considers spatial dependence originating from unobserved factors. Meanwhile, Geographically Weighted Regression (GWR) allows the relationship between variables to vary across locations (Anselin, 1988); (Brunsdon, Fotheringham, & Charlton, 1998). Previous studies have applied SAR and SEM to examine spatial patterns in various fields, including poverty, health outcomes, and regional development indicators (Anekawati, Purhadi, Rofik, & Hidayat, 2024); (Ayudia & Putri, 2024); (Prihadyatama, Nugroho, Kurniawan, & Haning, 2024); (Haris, Pradini, & Khudori, 2025);

(Pebriyanti, Hafid, & Sudarmin, 2025); (Shafira & Ariyanto, 2026). Similarly, GWR has been used to identify spatial variations in the determinants of regional phenomena, such as COVID-19 cases and childhood health problems (Suciptawati, Sugiantari, & Susilawati, 2023); (Putri, Suciptawati, & Susilawati, 2023).

Despite the increasing application of spatial models, research examining household financial distress from a spatial perspective remains limited. Previous studies have generally focused on household socioeconomic characteristics without considering whether financial vulnerability forms geographical patterns or is influenced by surrounding locations. This limitation is particularly relevant in areas undergoing major development transformation, where infrastructure changes and economic restructuring may affect households differently depending on their location.

Therefore, this study aims to analyze the determinants and spatial patterns of household financial distress in Sepaku District, North Penajam Paser Regency, amid the development dynamics of IKN. This research applies and compares several analytical approaches, including OLS, SAR, SEM, and GWR, to identify the most appropriate model for explaining household financial distress while considering spatial dependence and regional characteristics.

RESEARCH METHOD

Materials and Data

Primary data for this study came from surveys of Sepaku District residents in North Penajam Paser Regency. Since the expansion of Nusantara Capital City (IKN) has had an immediate effect on Sepaku District, altering infrastructure, economic activity, and household living conditions, it was selected as the site of the research. The homes in Sepaku District were made up of the sample population for this research. The Slovin formula was used to compute the sample size, which came out to 389 residences, with a margin of error of 5%. The degree of financial difficulty and associated socioeconomic factors were determined for each home as the unit of research. family income, education level of the head of the family, work status, number of dependents, distance to the nearest economic center, and road accessibility were the explanatory factors, while household financial distress was the dependent variable.

Data Analysis Techniques

1. Instrument Validity and Reliability Test

The study instrument's reliability was assessed using the Pearson Product Moment correlation method (Pearson, 1895). Using this technique, we can determine how each survey item contributes to the overall score. Here is the formula for calculating the Pearson correlation coefficient:

$$r_{AB} = \frac{N\sum AB - (\sum A)(\sum B)}{\sqrt{[N\sum A^2 - (\sum B)^2][N\sum A^2 - (\sum B)^2]}} \quad (1)$$

for which N is the total number of observations and r_{AB} is the item-to-total score correlation, A represents the score of each questionnaire item, B represents the total score of all questionnaire items, and $\sum A\,B$ represents the sum of the products between item scores and total scores.
The hypotheses for the validity test are:
$H_0: r_{AB} = 0$ (the questionnaire item has no significant relationship with the total score)
$H_1: r_{AB} \neq 0$ (the questionnaire item has a significant relationship with the total score)
If $| r_{hitung} | \leq r_{tabel}$, then H_0 is not rejected and the questionnaire item is considered invalid.

Using Cronbach's Alpha, which measures the internal consistency of indicators, the reliability of the instrument was tested (Cronbach, 1951):

$$R = \frac{m}{m-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_t^2}\right) \quad (2)$$

this is where R stands for the Cronbach's Alpha reliability coefficient, m denotes the number of indicators or items, $\sum \sigma_i^2$ denotes the total variance of each item in the questionnaire, and σ_t^2 is the total variance of all items in the questionnaire. The trustworthiness of the instrument is demonstrated by the Cronbach's Alpha value, which is above the permitted threshold.

2. Linear Regression Modeling Using Ordinary Least Squares (OLS)

In order to examine the relationship between the dependent and independent variables before including spatial effects, the OLS model was utilized as a baseline. Here is the basic outline of the OLS model: (Gujarati & Porter, 2009).

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad (3)$$

the dependent variable vector is represented by $\boldsymbol{Y}$, the independent variable matrix by $\boldsymbol{X}$, the regression coefficient vector by $\boldsymbol{\beta}$, and the error term by $\boldsymbol{\varepsilon}$.

3. Testing the Classical Assumptions of the Ordinary Least Squares (OLS) Regression Model

A battery of classical assumption tests were run on the OLS model to ensure the regression estimates were accurate before spatial regression models were used. The reason for these tests is that in order to assess the regression coefficients using the OLS approach, a number of assumptions must be satisfied (Gujarati & Porter, 2009). Tests for residual normality, multicollinearity, heteroscedasticity, and autocorrelation were utilized in this work.

The normality of regression residuals was examined using the Kolmogorov–Smirnov (K-S) test. This test evaluates whether the residual values follow a normal distribution. The hypotheses were formulated as follows:
$H_0: e_i \sim N(0, \sigma^2)$ (regression residuals are normally distributed)
$H_1: e_i \sim N(0, \sigma^2)$ (regression residuals don't follow a normal distribution)
H_0 is rejected if the calculated value of the Kolmogorov–Smirnov statistic D exceeds the critical value $D_{(\alpha,N)}$. This indicates that the residuals do not follow a normal distribution.

To check for possible multicollinearity among the independent variables, we used the Variance Inflation Factor (VIF) in conjunction with the tolerance parameters. When there is a strong linear relationship between explanatory variables, it is called multicollinearity. This

phenomenon might make regression findings less stable. A VIF value below 10 indicate that the model does not experience serious multicollinearity problems.

To identify heteroscedasticity in the regression model, the Breusch-Pagan test was utilized. The test's hypothesis was:

$H_0: \sigma_1^2 = \sigma_2^2 = \ldots = \sigma_n^2$ (the residuals have constant variance/homoscedasticity)

$H_1: \sigma_i^2 \neq \sigma_j^2$ (the residuals have unequal variance/heteroscedasticity)

H_0 is rejected if the calculated Breusch–Pagan statistic BP exceeds the critical value $\chi^2_{\alpha,k}$. This indicates that the regression model suffers from heteroscedasticity.

Finally, the Durbin–Watson (DW) statistic was used to examine autocorrelation among regression residuals. The hypotheses were:

$H_0: \rho_e = 0$ (no autocorrelation exists among the residuals)

$H_1: \rho_e \neq 0$ (autocorrelation exists among the residuals)

H_0 is rejected if the value of DW falls within the rejection region, indicating the presence of autocorrelation in the regression model.

4. Spatial Dependence Testing

Spatial dependence analysis was conducted to determine whether household financial distress showed a spatial pattern across observation areas. Before performing spatial autocorrelation analysis, the spatial relationship among households was defined through a spatial weight matrix. In this study, the spatial weight matrix was constructed using the K-Nearest Neighbor (KNN) approach, where neighboring observations were determined based on the closest geographical distance.

The presence of spatial dependence was initially examined using Moran's I statistic. This statistic evaluates whether observations with similar values tend to be located near each other or are randomly distributed across space. The Moran's I formulation is expressed as:

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(z_i)(z_j)}{\sum_{i=1}^{N} z_i^2} \quad (4)$$

where I represents the Moran's I statistic, N denotes the number of observations, w_{ij} represents the spatial weight between location i and location j, z_i represents the standardized value of the variable at location i, z_j denotes the standardized value of the variable at location j, and S_0 represents the sum of all spatial weights.

The hypotheses tested in Moran's I analysis were:

$H_0: I = E(I)$ (no spatial autocorrelation exists in the research data)

$H_1: I \neq E(I)$ (spatial autocorrelation exists in the research data)

A significant Moran's I result indicates that household financial distress has a spatial structure rather than being randomly distributed among locations.

To further examine the distribution pattern at the local level, Local Indicators of Spatial Association (LISA) analysis was performed. LISA identifies areas with similar or contrasting characteristics compared with their neighboring locations. The resulting spatial associations

were categorized into four groups: High–High (HH), Low–Low (LL), High–Low (HL), and Low–High (LH).

Once geographical dependency was established, the inclusion of spatial effects in the regression model was evaluated using Lagrange Multiplier (LM) tests. The LM-lag test was used to examine whether the dependent variable was affected by spatial interaction, while the LM-error test was used to assess spatial dependence contained in the error component. The hypotheses for LM tests were formulated as follows:

LM-Lag Test

$H_0: \rho = 0$ (no spatial lag effect exists in the model)

$H_1: \rho \neq 0$ (a spatial lag effect exists in the model)

LM-Error Test

$H_0: \lambda = 0$ (no spatial dependence exists in the error component)

$H_1: \lambda \neq 0$ (spatial dependence exists in the error component)

The LM test results were subsequently used as a consideration in selecting the appropriate spatial regression specification, particularly between the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM).

5. Spatial Regression Modeling

Three geographical regression models were calculated to take geographic influences into consideration: The SAR, SEM, and GWR models are all those that deal with spatial regression. The SAR model is expressed as: (Anselin, 1988)

$$\boldsymbol{Y} = \rho \boldsymbol{WY} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad (5)$$

in which $\boldsymbol{Y}$ stands for the dependent variable vector, ρ for the spatial dependence coefficient, $\boldsymbol{W}$ for the KNN spatial weight matrix, $\boldsymbol{WY}$ for the spatial lag of the dependent variable from nearby locations, $\boldsymbol{X}$ for the independent variable matrix, Π for the regression coefficient vector, and ε for the model error.

This is how the SEM model is stated:

$$\boldsymbol{Y} = \boldsymbol{X\beta} + u \text{ with } u = \lambda \boldsymbol{Wu} + \boldsymbol{\varepsilon} \quad (6)$$

where $\boldsymbol{W}$ denotes the spatial weight matrix, λ the spatial error dependence coefficient, $\boldsymbol{\varepsilon}$ the random error term, and $\boldsymbol{u}$ the spatial error component.

One way to describe the GWR model is as:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k (u_i, v_i) X_{ki} + \varepsilon_i \quad (7)$$

where Y_i represents the dependent variable at location i, (u_i, v_i) denotes the geographical coordinates of location i, $\beta_0(u_i, v_i)$ represents the local intercept, $\beta_k(u_i, v_i)$ denotes the local coefficient of the k-th independent variable at location i, X_{ki} represents the k-th independent variable at location i, and ε_i represents the error term at location i.

6. Selection of the Best Model

The model with the lowest Akaike Information Criterion (AIC) is considered the most appropriate, as it balances goodness-of-fit and parsimony. The AIC is calculated as follows: (Kubara & Kopczewska, 2023).

$$AIC = -2\ln(L) + 2k \quad (8)$$

where AIC represents the Akaike Information Criterion, L denotes the likelihood value of the model, and k represents the number of estimated parameters in the model.

RESULT AND DISCUSSION

Validity and Reliability Test

To establish the reliability of the research instrument, the Pearson Product-Moment Correlation Test was applied. The results showed that the item correlation coefficients (r_{AB}) exceeded the critical value $r_{(0.05,28)}$ = 0.361, ranging from 0.593 to 0.725. Furthermore, the p-values for all items were significantly below the 5% threshold, between 0.000 and 0.001. These findings confirm that all measurement items possess adequate validity and can appropriately represent the research variables. The reliability of the instrument was further assessed using Cronbach's Alpha to evaluate internal consistency among items. The study produced a Cronbach's Alpha coefficient of 0.643, which is above the acceptable minimum of 0.60. This result indicates that the instrument is sufficiently reliable and consistently measures the variables under investigation.

Spatial Distribution of Household Financial Distress

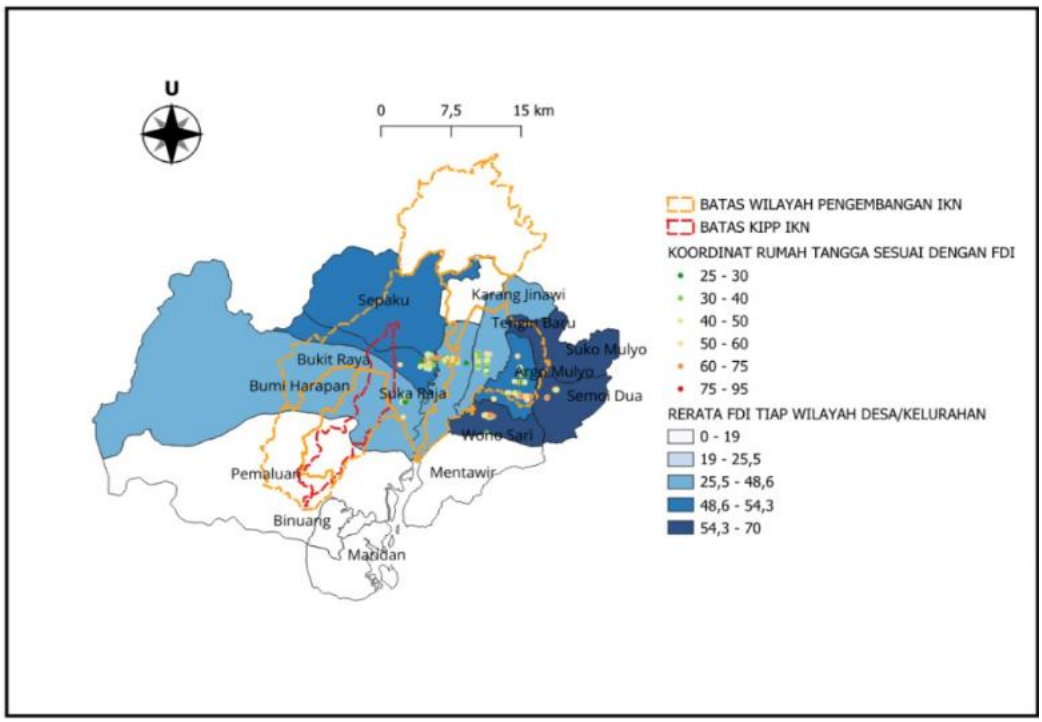


Figure 1. Spatial distribution map of household financial distress in north penajam paser regency

Based on the spatial analysis, the distribution of the Household Financial Distress Index (FDI) in North Penajam Paser Regency demonstrates substantial variation in household economic conditions across different areas. Relatively high FDI values are observed in several locations, including Suko Mulyo, Argomulyo, Semoi Dua, and Wonosari, which are situated within the development area of the Nusantara Capital City (IKN). This finding indicates that accelerated regional development has not yet resulted in an equal improvement in household economic conditions, as certain communities continue to experience economic pressures.

Conversely, areas with relatively lower FDI values are identified in several locations, including Sepaku, Bukit Raya, Bumi Harapan, and Sukaraja. These areas have spatial proximity to the Government Core Area (Kawasan Inti Pusat Pemerintahan/KIPP) of IKN and other IKN development zones. The presence of infrastructure development and emerging economic activities in these areas provides new economic opportunities for local communities; however, the extent of these benefits remains influenced by each household's capacity to access and utilize available economic opportunities.

The spatial distribution of FDI values further indicates that geographical proximity to the IKN development center does not directly determine household economic conditions. Areas located near the KIPP of IKN and surrounding development zones still exhibit variations in household FDI levels. This finding suggests that socioeconomic factors play an important role in shaping household financial distress conditions.

Spatially, the mapping results reveal the presence of clustering patterns among areas with similar FDI characteristics. Several locations within the IKN development transformation zone continue to demonstrate the presence of households with relatively high FDI values. These findings highlight the importance of ensuring economic inclusiveness in the IKN development process, so that spatial transformation and emerging economic activities not only promote regional growth but also contribute to improving household welfare in surrounding communities.

Diagnostic Tests for the Ordinary Least Squares (OLS) Regression Model

To make sure the model was fitting the classical assumptions, we ran a battery of diagnostic tests before looking at the OLS regression results. The results may be shown in Table 1.

Table 1. Diagnostic tests of the ols regression model

Diagnostic Test	Test Statistic	Critical Value	Decision	Conclusion
Multicollinearity (VIF)	VIF = 1.0184–1.0814	VIF < 10	Fail to reject H_0	No multicollinearity problem
Normality (Kolmogorov–Smirnov)	$D = 0.0439$; p-value = 0.0691	$D_{0.05,389} = 0.0690$	Fail to reject H_0	Residuals are normally distributed

Heteroscedasticity (Breusch–Pagan)	BP = 13.5310; df = 17; p-value = 0.7000	$\chi^2_{(0.05,17)}$ = 25.5870	Fail to reject H_0	Homoscedasticity assumption is satisfied
Autocorrelation (Durbin–Watson)	DW = 1.9298 p-value = 0.2411	d_U = 1.84 $4d_U$ = 2.16	Fail to reject H_0	No autocorrelation exists

Based on the diagnostic test results presented in Table 1, the OLS model satisfies all classical assumptions, including normality, absence of multicollinearity, homoscedasticity, and no autocorrelation. These results indicate that the estimated model is statistically reliable and can be used for further analysis. Furthermore, the absence of heteroscedasticity indicates that the model does not meet the heterogeneity criterion for applying the GWR approach. Thus, the homoscedasticity assumption is satisfied, and the analysis was not continued using the GWR model based on this criterion.

OLS Linear Regression Model

Table 2. Estimation parameter of ols linear regression model

Variable	Coefficient	Std. Error	*t-value*	*p-value*
Intercept	64.4066	4.8257	13.347	$< 2\times 10^{-16}$
Household Income2	-7.2211	2.1114	-3.420	0.000696
Household Income3	-12.1861	2.1495	-5.669	2.89×10^{-8}
Household Income4	-11.1653	2.6369	-4.234	2.90×10^{-5}
Household Income5	-18.3536	2.6839	-7.018	1.08×10^{-11}
Educational Level of Household Head2	1.3526	3.0992	0.436	0.662762
Educational Level of Household Head3	1.2510	3.3107	0.378	0.705752
Educational Level of Household Head4	0.8933	3.3333	0.268	0.788842
Educational Level of Household Head5	1.0573	3.9784	0.266	0.790574
Occupation of Household Head2	1.3856	2.9400	0.471	0.637721
Occupation of Household Head3	-1.2600	3.2190	-0.391	0.695721
Occupation of Household Head4	-3.1659	3.3208	-0.953	0.341025
Occupation of Household Head5	7.5381	12.4266	0.607	0.544483
Number of Household Dependents	0.7933	0.4550	1.743	0.082097
Travel Time to the Nearest Economic Center	-0.1860	0.1024	-1.817	0.069963
Road Accessibility2	-0.4023	3.4064	-0.118	0.906055
Road Accessibility3	-3.9577	3.2658	-1.212	0.226335
Road Accessibility4	-9.9812	3.3109	-3.015	0.002750

Based on the linear regression results presented in Table 2, the variables that significantly influence Household Financial Distress (Y) at the 5% significance level ($\alpha = 0.05$) are Household Income and Road Accessibility. The Household Income categories (Income2, Income3, Income4, and Income5) show negative and significant effects compared with the reference category (Income ≤ Rp1,000,000). The coefficients are -7.2211 (p-value = 0.000696), -12.1861 (p-value < 0.001), -11.1653 (p-value < 0.001), and -18.3536 (p-value < 0.001), respectively. These results point to a correlation between higher household income and reduced financial stress. Greater road accessibility reduces family financial hardship by strengthening links to markets and economic activities; this is supported by Road Accessibility4, which also has a negative and statistically significant effect (r=-9.9812, p= 0.002750). Concurrently, there is no statistically significant relationship between the educational level, occupation, number of dependents in the household, and travel time to the nearest economic center (p-value > 0.05) of the household head.

The estimated regression model is expressed as:

$$\begin{aligned} Y = {} & 64.4066 - 7.2211Income2 - 12.1861Income3 - 11.1653Income4 \\ & - 18.3536Income5 + 1.3526Education2 + 1.2510Education3 \\ & + 0.8933Education4 + 1.0573Education5 + 1.3856Occupation2 \\ & - 1.2600Occupation3 - 3.1659Occupation4 + 7.5381Occupation5 \\ & + 0.7933Dependents - 0.1860Time - 0.4023Accessibility2 \\ & - 3.9577Accessibility3 - 9.9812Accessibility4 \end{aligned}$$

The independent variables may explain 30.86% of the dependent variable's variation, according to the model's assessment findings, which indicates an R^2 value of 0.3086. Factors outside of the model account for the rest of the variance. With a p-value lower than 0.05 and an F-statistic greater than 9.74, the results of the simultaneous tests show that the significance level is higher than the critical value of $F_{0.05,17,371}$=1.650. It follows that H_0 is rejected since the independent variables collectively impact the dependent variable in a meaningful way. These findings confirm that the linear regression model is statistically appropriate and can be used to explain the relationship among the variables investigated in this study.

Spatial Dependence Analysis

Spatial dependence analysis was conducted to examine whether household financial distress exhibited spatial patterns across locations. The global spatial autocorrelation was determined using the Moran's I test before LISA analysis was used to discover local clustering patterns. Optimal results from the spatial regression were also obtained by using the Lagrange Multiplier (LM) test. A result of 0.1157 and a p-value of 4.25×10^{-16} were produced using the Moran's I test. Since we can no longer accept that there is no geographical autocorrelation, we may safely assume that there is substantial spatial reliance. regions with low levels of household financial hardship tend to cluster with other low-distress regions, whereas those with high levels

of hardship are likely to be surrounded by areas with similar situations, according to the positive Moran's I value.

The LISA analysis identifies local spatial clustering patterns of household financial distress. The results show that 59 households are classified as High–High (HH) clusters, indicating areas with high financial distress surrounded by neighboring households experiencing similar conditions. Meanwhile, 38 households belong to the Low–Low (LL) category, representing areas with relatively lower financial distress. Spatial outliers are identified through the High–Low (HL) pattern (15 households) and Low–High (LH) pattern (21 households), indicating differences between individual locations and their surrounding areas. These results further support the existence of spatial clustering in household financial distress.

Next, we utilized the LM test to figure out which spatial regression parameters were appropriate. With p-values of 0.0052 and 5.494 x 10^{-6}, respectively, the LM Lag and LM Error tests reveal significant spatial effects. Having said that, the Robust LM Lag test does show significance (p-value = 9.237 x 10^{-5}), however the Robust LM Error test does not (p-value = 0.1183). Based on these findings, next research should employ the geographical Autoregressive Model (SAR) to determine if a spatial lag effect is the most appropriate representation of geographical reliance.

Model Performance Evaluation and Selection

Table 3. Model comparison

Model	AIC
OLS	3050.930
SAR	3040.495
SEM	3046.440

The comparison of model performance shows that the SAR model provides the lowest Akaike Information Criterion (AIC) value (3040.495) compared with SEM (3046.440) and OLS (3050.930). Therefore, SAR was selected as the most appropriate model for explaining household financial distress because it better captures spatial relationships among observations.

Spatial Autoregressive Model (SAR) Model

Table 4. Estimation parameter of sar model

Variable	Coefficient	Std. Error	*t-value*	*p-value*
Intercept	42.7814	7.2429	5.9067	0.0000
Household Income 2	-6.9373	2.0242	-3.4273	0.0006
Household Income 3	-12.2112	2.0594	-5.9294	0.0000
Household Income 4	-10.8161	2.5297	-4.2757	0.0000
Household Income 5	-18.8178	5.2717	-3.3174	0.0009

Educational Level of Household Head 2	0.9102	2.9717	0.3063	0.7594
Educational Level of Household Head 3	0.8748	3.1729	0.2757	0.7828
Educational Level of Household Head 4	0.6262	3.1941	0.1961	0.8446
Educational Level of Household Head 5	0.2960	3.8148	0.0776	0.9382
Occupation of Household Head 2	1.5613	2.8177	0.5541	0.5795
Occupation of Household Head 3	-0.3707	3.0867	-0.1201	0.9044
Occupation of Household Head 4	-2.7277	3.1839	-0.8567	0.3916
Occupation of Household Head 5	6.6406	11.9043	0.5578	0.5769
Number of Household Dependents	0.7949	0.4362	1.8222	0.0684
Travel Time to the Nearest Economic Center	-0.1696	0.0981	-1.7290	0.0838
Road Accessibility 2	1.2026	3.2749	0.3672	0.7135
Road Accessibility 3	-0.8897	3.1822	-0.2796	0.7798
Road Accessibility 4	-6.4245	3.2331	-1.9871	0.0469
ρ	0.3610	0.0987	3.6579	0.0003

Based on the estimation results of the SAR presented in Table 4, the spatial coefficient (ρ) is estimated at 0.3610, with a z-statistic value of 3.6579 and a p-value of 0.0003. This result indicates the presence of positive and statistically significant spatial dependence in household financial distress. The positive spatial coefficient suggests that financial distress in one area is associated with similar conditions in neighboring areas. Therefore, household financial conditions are not only influenced by internal socioeconomic characteristics but are also affected by the conditions of surrounding areas.

The variables that significantly influence household financial distress are Household Income and Road Accessibility. All categories of Household Income (Income2, Income3, Income4, and Income5) show negative and significant effects compared with the reference category. These results indicate that households with higher income levels tend to experience lower financial distress, reflecting greater capacity to meet basic needs and cope with economic pressures. For Road Accessibility, only Access4 shows a negative and significant effect on household financial distress, indicating that better accessibility conditions are associated with reduced financial pressure through improved access to economic activities, markets, and employment opportunities. Meanwhile, other accessibility categories do not show significant effects.

The variables Educational Level of Household Head, Occupation of Household Head, Number of Household Dependents, and Travel Time to the Nearest Economic Center do not show statistically significant effects (p-value > 0.05). Overall, the SAR model indicates that household income, specific accessibility conditions, and spatial interactions are important factors explaining variations in household financial distress.

The following is the form of the spatial regression model based on the results of the SAR estimate:

$$Y = 0.3610WFD_i + 42.7814 - 6.9373Income2 - 12.2112Income3 \\ -10.8161Income4 - 18.8178Income5 \\ +0.9102Education2 + 0.8748Education3 \\ +0.6262Education4 + 0.2960Education5 \\ +1.5613Occupation2 - 0.3707Occupation3 \\ -2.7277Occupation4 + 6.6406Occupation5 \\ +0.7949Dependents - 0.1696Time \\ +1.2026Accessibility2 - 0.8897Accessibility3 \\ -6.4245Accessibility4 + \varepsilon_i$$

CONCLUSION AND SUGGESTION

This study demonstrates that household financial distress exhibits spatial dependence across regions. Indicating a connection between the financial hardship situation in one area and conditions in other places, the empirical data reveals the existence of positive spatial autocorrelation. With an Akaike Information Criterion (AIC) value of 3040.495, the Spatial Autoregressive Model (SAR) outperforms the Spatial Error Model (SEM) (3046.440) and the Ordinary Least Squares (OLS) model (3050.930) in terms of suitability, according to results from model comparisons. The SAR estimation results indicate that household income and road infrastructure accessibility have a negative and significant effect on household financial distress. These findings suggest that household resilience in facing economic pressures is not solely determined by internal household characteristics but is also influenced by the socioeconomic conditions and spatial environment in which households are located.

Based on these findings, local governments and relevant stakeholders should place greater emphasis on strengthening household economic capacity and income generation, as income consistently emerges as a significant determinant of financial distress levels. Policies related to income improvement, community economic empowerment, employment opportunities, and the strengthening of local businesses should be prioritized, particularly in areas experiencing relatively higher levels of financial distress. Furthermore, improving infrastructure accessibility and supporting economic connectivity should become integral components of regional development strategies. The results indicate that road accessibility (Access4) has a negative and significant effect on financial distress, implying that improvements in road quality and connectivity between communities and economic centers may contribute to reducing household financial pressures.

Given the existence of positive spatial dependence, strategies for mitigating household financial distress should not be implemented solely at the individual household or isolated regional level. Interventions in one area should consider the conditions of surrounding areas to generate broader and more integrated impacts. Spatially coordinated policies are therefore essential to address financial vulnerability within the context of regional transformation, particularly in areas affected by the development of the Nusantara Capital City (IKN). For future research, longitudinal data analysis is recommended to capture changes in household

financial distress over time, particularly in response to the ongoing development of IKN. Future studies may also incorporate additional variables, such as financial management behavior, asset ownership, economic adaptation strategies, and policy support mechanisms. Moreover, expanding the geographical scope of the research area may improve the generalizability of the findings.

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