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Comparative Study of Conventional and Spatial Panel Models in Analyzing the Information and Communication Technology Development Index

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Abstract Indonesia continues to face digital inequality, both in terms of inter-provincial disparities and in comparison, to other countries in Southeast Asia, where it lags behind Vietnam and is far below Singapore. These disparities highlight spatial heterogeneity, where regional characteristics influence by Information and Communication Technology (ICT) capacity differently, and spatial dependence, where development in one province can spill over to others. Given the strategic importance of ICT in driving sustainable growth, overcoming such inequality is crucial. This challenge is also strongly linked to SDG 9 and SDG 10, which emphasize inclusive digital development as a pathway to reducing gaps across regions. This research seeks to examine the determinants affecting Information and Communication Technology Development Index (ICT-DI) across Indonesian province by contrasting traditional panel data models with spatial panel modeling techniques. Secondary data from Central Bureau of Statistics (Indonesia) for 2020-2023 were used. Descriptive analysis and thematic mapping were conducted, followed by estimation using the panel model, as well as spatial panel models including Spatial Autoregressive Fixed Effect (SAR-FE) and Spatial Error Model Fixed Effect (SEM-FE). The results indicate significant spatial dependence across provinces, confirming the relevance of spatial analysis. The SAR-FE model was identified as the best model, explaining 98.47% of the variation in ICT-DI with the lowest MAPE value (1.1023). Population density was identified as the only significant positive factor, indicating that more densely populated regions tend to have better ICT infrastructure and capacity.The findings emphasize the novelty of applying spatial panel models to ICT analysis in Indonesia and underline their policy relevance, showing that accounting for spatial dependence and regional heterogeneity enables policymakers to design inclusive and sustainable, province specific strategies, such as leveraging population concentration in Southeast Sulawesi through digital hubs while addressing connectivity constraints in Bangka Belitung to reduce digital inequality.

Keywords Digital Inequality, ICT Development Index, Panel Model, Spatial Panel Models, Sustainable Infrastructure Development.

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1. Introduction

Digital disparity is one of the factors that reflects the differences in people's ability to access and utilize ICT in Indonesia. To address this issue, the ICT-DI was developed by the Central Bureau of Statistics (BPS) based on the International Telecommunication Union (ITU) framework, becoming an important tool for measuring the digital capacity of a region through three main dimensions, namely ICT infrastructure access, technology use, and digital skills, which are assessed using a composite score on a scale of 1–10, making it easier to compare between provinces and between periods [1].

Over the past four years, the progression of ICT-DI scores across Indonesia exhibited an upward tendency, though the improvement remained uneven among regions. According to information released by the BPS, Indonesia's national ICT-DI in 2020 was 5.56, which then rose to 5.78 in 2021, 5.88 in 2022, and 5.98 in 2023 [2, 3]. During

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this period, provinces such as DKI Jakarta and DI Yogyakarta ranked at the top with an ICT-DI score of 7.46 in DKI Jakarta in 2020, rising to 7.73 in 2023, and in DI Yogyakarta, the score was 7.09 in 2020, rising to 7.26 in 2023. Meanwhile, other provinces such as Papua and East Nusa Tenggara lag far behind with low ICT-DI values of 3.44 in 2023 in Papua and 5.33 in 2023 in East Nusa Tenggara [4]. In addition, based on the ICT-DI 2024 report by ITU, Indonesia has a score of 82.8 out of 100, which is lower than Vietnam's score of 85 and far below Singapore's score of 97.8, which ranks first in the Southeast Asia region [5]. This shows that Indonesia still faces challenges in increasing the average value, but also in reducing the disparity between regions.

Various factors can influence the level of ICT in a region. An example of this factor can be seen in the conditions of a region, where areas with a large productive-age population in a region have the potential to adopt technology more quickly, while areas with high population density tend to have ICT infrastructure due to the efficiency of service distribution [6]. In addition, the availability of basic infrastructure such as equitable access to electricity is a key prerequisite before digital technology can be optimally utilized [7]. Other factors on the usage side, such as the percentage of households that accessed the internet in the last three months and mobile phone ownership or usage, are important indicators that describe the level of ICT in society [8]. The combination of demographic factors, infrastructure, and usage habits forms an ecosystem that determines how quickly or slowly a region can catch up with digital inequality.

Several previous studies have been conducted to analyze the influence of several factors on ICT-DI. A study examining the influence of information and communication technology on poverty rates in Indonesia during the period 2012–2017 was conducted using panel data analysis, which produced results showing that the Random Effect Model (REM) regression model had been selected, with one among the variables that has a negative and significant relationship with poverty levels being ICT-DI and the percentage of households with access to electricity [9]. Other studies using panel analysis methods show that there is a significant influence where ICT-DI, along with other components such as the use or ownership of landline telephones, computers, mobile phones, the internet, and infrastructure, affects the reduction of educational inequality in Indonesia, with the best model for panel analysis being the Fixed Effect Model (FEM), which proves the need for further analysis of ICT, especially regarding the ownership or use of telephone modems and infrastructure [10]. Other studies conducted outside Indonesia, such as in China, show spatial dependence on ICT sector activities analyzed using SAR and SEM models [11]. Furthermore, a study of the Russian digital data economy covering more than 80 regions shows that SAR and SEM models are able to explain regional variations in digital indicators and economic growth, supporting the use of classic spatial panel models without independent variable lags [12]. Then, in the European Union, the use of SAR models in assessing the impact of ICT and AI investments reinforces the evidence that cross-regional spatial dependence systematically affects digital outcomes [13].

Previous studies have been limited to conventional panel analysis without considering spatial relationships between regions, even though regional relationships are very important to consider and can be analyzed using spatial analysis methods. There are many types of spatial analysis methods, including Kriging, Geographically Weighted Regression, Spatial Smoothing, Spatial Autocorrelation, and even a combination of spatial panel methods [14]. Spatial models introduce two important assumptions. First, spatial dependence, which implies that ICT in one province can be influenced by or spill over into neighboring provinces [15]. Second, spatial heterogeneity, which highlights the diversity of regional characteristics, meaning that the effect of explanatory variables may vary across provinces due to differences in demographic, economic, and geographic contexts [16]. From both assumptions, spatial modeling not only captures temporal dynamics as in conventional panel analysis but also provides deeper insight into how regional interactions and local specificities shape the ICT-DI.

To overcome the limitations of previous studies, the application of spatial panel methods is proposed to combine data variations between regions and over time while explicitly considering geographical relationships [17]. The two main models in this approach are the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM). This method has the advantage of capturing direct and indirect effects between regions, as well as producing a more accurate understanding than conventional panel models [18]. In the use of spatial panel methods, the main SAR model is able to explicitly model spatial dependence on dependent variables, thereby identifying the extent to which the development of ICT in a province is influenced by conditions in surrounding provinces [19]. SAR modeling can also provide clearer and more targeted implications for policymaking based on ICT-DI analysis results.

Using the spatial panel analysis method to analyze the factors that influence the ICT-DI between provinces in Indonesia is very necessary, considering spatial interrelationships, and testing the relevance of each factor for improving the index and providing recommendations to reduce digital inequality in each region in Indonesia. This is in accordance with the Sustainable Development Goals (SDGs), particularly SDG 9 (*Industry, Innovation, and Infrastructure*) on fostering infrastructure, inclusive industrialization, and innovation through expanded ICT access, and supports SDG 10 (*Reduced Inequalities*) by reducing inter-regional disparities via equitable digital access [20, 21]. This research can also be used as a reference for policymakers and other relevant parties in formulating inclusive and sustainable ICT development strategies, explicitly considering spatial dependence and heterogeneity, so that each province can design local policies tailored to its dominant factors and priorities in improving the ICT-DI.

This study provides the first application of a spatial panel model to analyse provincial-level ICT-DI data in Indonesia and comparing it with the conventional panel method, involving the variables of Number of Productive Age Population and Population Density as novelties. The working-age population was chosen because it reflects the potential contribution to economic activity and technology utilisation, while population density describes the intensity of settlement that influences the spread of technology between regions.

2. Research Methods

2.1. Data and Variable

The data utilized in this research consist of secondary data from BPS regarding the ICT-DI from 2020–2023 from all provinces in Indonesia. The research variable used is the ICT-DI as dependence variable, Number of Productive Age Population, Population Density, Percentage of Households with Access to Electricity, Percentage of Household that Accessed the Internet in the Last Three Months, and Percentage of Households that Own/Use Mobile Phones as independence variable. All variables are explained in the following Table 1.

Table 1. Research Variables Description

Variable	**Full Variable Name**	**Description**	**Unit**	**Data Source**
Y	Information and Communication Technology Development Index (ICT-DI)	A composite index measuring the level of information and communication technology development in a region, encompassing ICT access, usage, and skills	Index	Central Bureau of Statistics (BPS)
X_1	Number of Productive Age Population	Total population within the productive age range (15–64 years), representing potential contributors to economic activity and technology adoption	Persons	Central Bureau of Statistics (BPS)
X_2	Population Density	The concentration of population within a given area, indicating the intensity of human settlement	Persons/km^2	Central Bureau of Statistics (BPS)
X_3	Percentage of Households with Access to Electricity	Proportion of households with access to electricity as a fundamental infrastructure supporting ICT development	Percent (%)	Central Bureau of Statistics (BPS)
X_4	Percentage of Households that Accessed the Internet in the Last Three Months	Proportion of households that used the internet within the past three months, reflecting the level of digital engagement	Percent (%)	Central Bureau of Statistics (BPS)
X_5	Percentage of Households that Own/Use Mobile Phones	Proportion of households that own or use mobile phones as a primary means of digital communication	Percent (%)	Central Bureau of Statistics (BPS)

2.2. Research Procedure

The steps taken to analyze and compare ICT-DI against factor variables using the spatial panel method are as follows.

1. Analysis descriptive statistical data on research variable and create thematic map to describe presentation of ICT-DI every Province in Indonesia.
2. Conducting ICT-DI using panel data analysis
   (a) Parameter estimation within panel data model, using the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM).
   CEM can be written in equation (1):
$$y_{it} = \alpha + \sum_{k=1}^{K} \beta_k X_{kit} + \varepsilon_{it}, \quad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T \tag{1}$$
   FEM in equation (2):
$$y_{it} = \alpha_i + \sum_{k=1}^{p} \beta_k X_{kit} + \varepsilon_{it}, \quad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T \tag{2}$$
   REM in equation (3)
$$y_{it} = \beta_0 + \sum_{k=1}^{p} \beta_k X_{kit} + u_{it}, \quad i = 1, 2, \ldots, N;\ t = 1, 2, \ldots, T \tag{3}$$
   with $u_{it} = \mu_i + \varepsilon_{it}$, where y_{it} serves as the response variable for unit i at time t, α is the intercept, α_i is the intercept of the fixed individual regression model i, X_{kit} is the predictor variable k for unit i at time t, β_k is the slope coefficient, ε_{it} is the error term, and μ_i is the unobserved individual effect.
   (b) Performing Chow Test to identify the best model between CEM and FEM.
   Statistics of Chow Test in equation (4):
$$F = \frac{(RSS_{CEM} - RSS_{FEM})/(N-1)}{RSS_{FEM}/(NT - N - K)} \tag{4}$$
   where RSS_{CEM} is the sum of squares residual of CEM, RSS_{FEM} is the sum of squares residual of FEM, N is the count of cross-section units, T is the count of periods, and K is the count of parameters.
3. Conducting ICT-DI using Spatial Panel Data Analysis
   (a) Constructing a spatial weighting matrix using the inverse distance method.
   (b) Performing Moran's I test to test spatial dependence between regions. If spatial dependence is proven, proceed to the next stage.
   (c) Test the Lagrange Multiplier Test, that is LM_{SAR}, LM_{SEM}, robust LM_{SAR}, and robust LM_{SEM}.
   LM_{SAR} in equation (5):
$$LM_{\text{SAR}} = \frac{\left[(e'(I_T \otimes W)y)/\hat{\sigma}_e^2\right]^2}{J} \tag{5}$$
   and robust LM_{SAR} in equation (6):
$$RLM_{\text{SAR}} = LM_{\text{SAR}} - \frac{\left[\text{Cov}\left(LM_{\text{SAR}}, LM_{\text{SEM}}\right)\right]^2}{LM_{\text{SEM}}} \tag{6}$$
   where I_T is a $T \times T$ identity matrix; e is an $NT \times 1$ panel error vector model without spatial effects; $\hat{\sigma}_e^2$ is the panel error variance estimator;
   $J = \frac{1}{\hat{\sigma}_e^2}\left[((I_T \otimes W)X\hat{\beta})'(I_{NT} - X(X'X)^{-1}X')((I_T \otimes W)X\hat{\beta}) + TT_w\hat{\sigma}_e^2\right]$;
   $T_w = tr(WW + W'W)$;
   LM_{SEM} in equation (7):
$$LM_{\text{SEM}} = \frac{\left[(e'(I_T \otimes W)Y)/\hat{\sigma}_e^2\right]^2}{T \times T_w} \sim \chi^2_{\alpha(1)} \tag{7}$$

and robust LM_{SEM} in equation (8):

$$RLM_{\text{SEM}} = LM_{\text{SEM}} - \frac{\left[\text{Cov}\left(LM_{\text{SAR}}, LM_{\text{SEM}}\right)\right]^2}{LM_{\text{SAR}}} \tag{8}$$

where Y is the $N \times T$ response variable vector; $\hat{\sigma}_e^2 = (e'e)/(NT)$ is model error variance; T is the number of time periods.

(d) Parameter estimation using SAR-FE and SEM-FE to obtain coefficient estimation $\hat{\beta}$.
SAR-FE in equation (9):

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it}\beta + \mu_i + \varepsilon_{it} \tag{9}$$

where y_{it} serves as the dependent variable for unit i at time t; ρ is the spatial lag effect coefficient; μ_i is the specific spatial effect for unit i; w_{ij} is the spatial weighted matrix component W; X_{it} is a $1 \times p$ predictor vector, β is a $p \times 1$ regression coefficient vector; $\varepsilon_{it} \sim N(0, \sigma^2)$ is the residual.
By estimating SAR-FE using likelihood equation we can conduct $\hat{\mu}_i$ estimation in equation (10):

$$\hat{\mu}_i = \frac{1}{T} \sum_{t=1}^{T} (y_{it} - \rho \sum_{j=1}^{N} w_{ij} y_{jt} - X_{it}\beta), \quad i = 1, 2, \ldots, N \tag{10}$$

With $\hat{\mu}_i$ estimation we can find $\hat{\beta}$ estimation for SAR-FE in equation (12):

$$\begin{aligned} \ln L_y = &- \frac{NT}{2} \ln(2\pi\sigma^2) + T \ln |I_N - \rho W_N| \\ &- \frac{1}{2\sigma^2} \left(y^* - \rho(I_T \otimes W_N) y^* - X^*\beta\right)' \left(y^* - \rho(I_T \otimes W_N) y^* - X^*\beta\right) \end{aligned} \tag{11}$$

with

$$y_{it}^* = y_{it} - \frac{1}{T} \sum_{t=1}^{T} y_{it}; \quad X_{it}^* = X_{it} - \frac{1}{T} \sum_{t=1}^{T} X_{it}; \quad (Wy_t)_i^* = \sum_{j=1}^{N} w_{ij} y_{jt} - \frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{N} w_{ij} y_{js}$$

The equation for $\hat{\beta}$ is obtained by setting the derivative of the likelihood function in equation (11) with respect to β to zero.

$$\hat{\beta} = \left(X^{*\prime} X^*\right)^{-1} X^{*\prime} \left[y^* - \rho(I_T \otimes W_N) y^*\right] \tag{12}$$

with $\left(X^{*\prime} X^*\right)^{-1}$ is nonsingular.

(e) SEM-FE in equation (13):

$$y_{it} = X_{it}\beta + \mu_i + \phi_{it} \tag{13}$$

with

$$\phi_{it} = \lambda \sum_{j=1}^{N} w_{ij} \phi_{jt} + \varepsilon_{it}$$

where λ represents the spatial autocorrelation parameter, ϕ_{jt} represents the spatial error autocorrelation component for unit i at time t, β represents the slope coefficient vector of dimension $p \times 1$, and ε_{it} represents the error term for unit i at time t with the assumption $\varepsilon_{it} \sim N(0, \sigma^2)$.
By estimating SEM-FE using likelihood equation, we can conduct $\hat{\mu}_i$ estimation in equation (14):

$$\hat{\mu}_i = \frac{1}{T} \sum_{t=1}^{T} (y_{it} - X_{it}\beta), \quad i = 1, 2, \ldots, N \tag{14}$$

with $\hat{\mu}_i$ estimation, we can find $\hat{\beta}$ estimation for SEM-FE in equation (16):

$$\ln L_y = -\frac{NT}{2}\ln(2\pi\sigma^2) + T\ln|I_N - \lambda W_N| - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{y_{it}^* - \left[\lambda\sum_{j=1}^{N} w_{ij}y_{jt}\right]^* - \left[x_{it}^*\beta - \lambda\Big(\sum_{j=1}^{N} w_{ij}x_{jt}\Big)^*\beta\right]\right\}^2 \quad (15)$$

By setting the derivative of the likelihood function (15) in relation to β to zero, the subsequent equation is derived in equation (16):

$$\hat{\beta} = [X^* - \lambda(I_T \otimes W_N)X^*]'\,[X^* - \lambda(I_T \otimes W_N)X^*]^{-1}\,[X^* - \lambda(I_T \otimes W_N)X^*]'\,[y^* - \lambda(I_T \otimes W_N)y^*] \quad (16)$$

(f) Determining the best model based on the largest coefficient of determination (R^2) and the smallest MAPE.
Coefficient of Determination or (R^2) in equation (17):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} - \hat{y}_{it})^2}{\sum_{i=1}^{n}\sum_{t=1}^{T}(y_{it} - \bar{y}_i)^2} \quad (17)$$

Mean Absolute Percentage Error (MAPE) in equation (18):

$$MAPE = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left|\frac{y_{it} - \hat{y}_{it}}{y_{it}}\right| \quad (18)$$

where $\hat{y}_{it}$ is the expected value of unit i at time t for the response variable, and $\bar{y}_i$ is the average value of the response variable for unit i.
The MAPE values can be interpreted according to the range presented in Table 2 below.

Table 2. MAPE Value Criteria

MAPE	**Interpretation**
MAPE $<$ 10%	Highly accurate prediction
10% $\leq$ MAPE $<$ 20%	Good prediction
20% $\leq$ MAPE $\leq$ 50%	Reasonable prediction
MAPE $>$ 50%	Inaccurate prediction

(g) Test the assumptions of normality and heteroscedasticity in the selected model.
(h) Conduct individual tests on the selected model.
Individual test in equation (19):

$$t_j = \frac{\hat{\beta}_j}{Se(\hat{\beta}_j)} \quad (19)$$

where $\hat{\beta}_j$ is the estimated regression coefficient for predictor variable j and $Se(\hat{\beta}_j)$ is its standard error.

3. Result and Discussion

3.1. Description of ICT Development Index with Thematic

Based on Figure 1, the ICT-DI increased in the majority of Indonesian provinces between 2020 and 2023. While middle-ranking provinces in Sumatra, Java, and Kalimantan experienced moderate growth, developed provinces

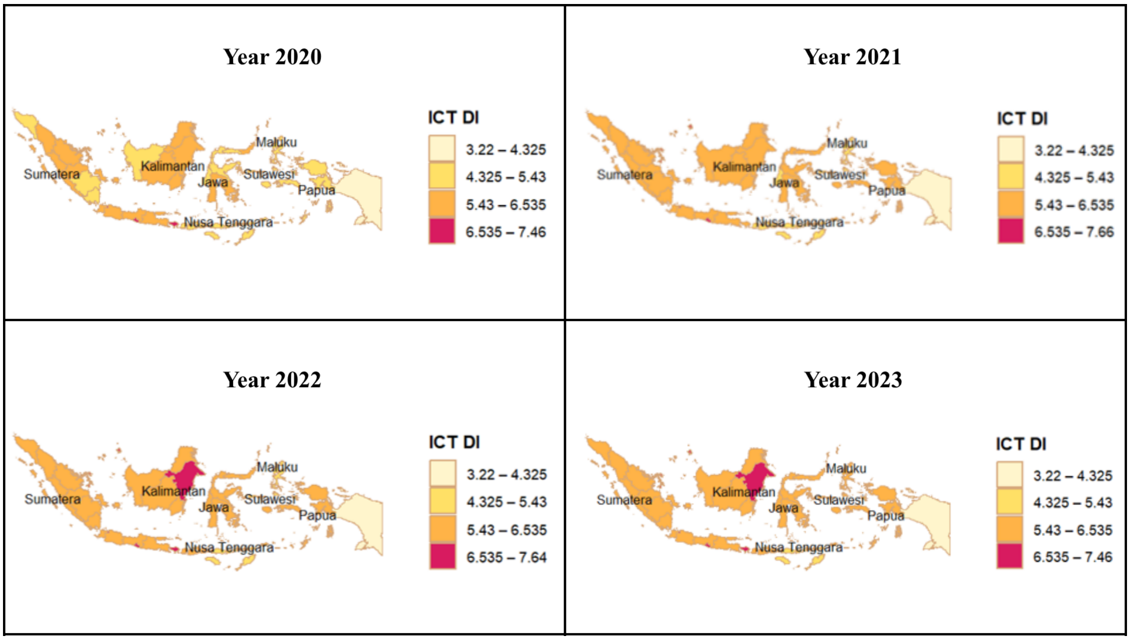

Figure 1. Thematic Map of Information and Communication Technology Development Index for 2020–2023

such as DKI Jakarta (7.46–7.73), Yogyakarta (7.09–7.26), Bali (6.57–6.60), and the Riau Islands (6.46–6.66) tended to remain stable at a high level. Even though Papua had the lowest score (3.35–3.44), underdeveloped provinces such as NTT (4.49–5.33), West Sulawesi (4.73–5.63), and North Maluku (4.78–5.56) demonstrated notable progress. With DKI Jakarta having the highest score and Papua the lowest, this pattern generally indicates a clear disparity in ICT development across provinces in Indonesia. This condition indicates the need for further analytical approaches to examine the inter-provincial linkage patterns and identify factors that influence ICT development, so that policy formulation can be carried out in a more targeted manner and oriented towards equitable distribution of ICT.

3.2. Panel Data Examination

The Chow test was performed at a 5% significance level to determine whether the within model/FEM, estimated using the within transformation, provides a better fit than pooled OLS/CEM. Prior to conducting the test, the estimation results of the pooled OLS should be found. The CEM estimation result is shown in Table 3.

Table 3. CEM Parameter Estimation Results

Variable	Coefficient	Significance
Intercept	7.2039	0.0000
X_1	0.0000	0.0000
X_2	0.0021	0.3514
X_3	0.0397	0.0000
X_4	0.0289	0.0624
X_5	0.0025	0.8799

Table 3 show that X_1 and X_3 significantly increase the ICT-DI, while X_2, X_4, and X_5 are not significant at a 5% significance level. The model's coefficient of determination (R^2) value of 15.48% indicates that the explanatory variables collectively account for 15.48% of the variation in the ICT-DI, with the remaining 84.52% impacted by additional variables not taken into the model. Additionally, the parameter estimates for FEM are presented as follows.

Table 4. FEM Parameter Estimation Results

Variable	**Coefficient**	**Significance**
X_1	0.0000	0.6537
X_2	0.0016	0.0044
X_3	-0.0159	0.1643
X_4	0.0222	0.0000
X_5	0.0191	0.0529

Based on Table 4, the coefficient of determination (R^2) value of 65.469% indicates that the explanatory variables can explain for the majority of the variance in the ICT-DI, whereas the remaining 34.531% is explained by other factors not included in the model. Variables X_2 and X_4 have positive and significant effects at the 5% significance level, while X_1, X_3, and X_5 do not show statistically significant effects on the ICT-DI. Furthermore, the random model/REM parameter estimates are expressed as follows.

Table 5. REM Parameter Estimation Results

Variable	**Coefficient**	**Significance**
Intercept	5.5527	0.0000
X_1	0.0000	0.0532
X_2	-0.0004	0.3989
X_3	-0.0332	0.0002
X_4	0.0266	0.0000
X_5	0.0164	0.0863

Based on Table 5, the random model explains 53.101% of the variation in the ICT-DI. At the 5% significance level, X_2 and X_5 show positive effects but are not statistically significant, X_2 shows a negative and insignificant effect, X_3 has a significant negative effect indicating that its increase tends to reduce the index, and X_4 has a significant positive effect suggesting that its increase is associated with a higher ICT-DI.

To identify the optimal panel data model, the Chow test was performed. The hypotheses for the Chow test are as follows:

$$H_0 : \beta_{01} = \beta_{02} = \cdots = \beta_{0n} = 0 \qquad \text{(The selected model is CEM)}$$

$$H_1 : \text{There is at least one } \beta_{0i} \neq 0, \quad i = 1, 2, \ldots, n \qquad \text{(The selected model is FEM)}$$

If the significance is less than 0.05, the FEM is used; otherwise, the CEM is applied. Alternatively, H_0 is rejected if

$$F_{\text{count}} > F_{(n-1;\, n(T-1)-k)}$$

The Chow test statistic is given by equation (20):

$$F_{\text{count}} = \frac{\left(R^2_{\text{LSDV}} - R^2_{\text{pooled}}\right)/(n-1)}{\left(1 - R^2_{\text{LSDV}}\right)/(nT - n - k)} \tag{20}$$

Table 6 indicates that H_0 is rejected at the 5% significance level with $F_{\text{count}} > F_{\text{table}}$, implying that the model contains one or more individual effects and thus follows the within model.

Table 6. Chow Test Results

Df1	**Df2**	F_{count}	F_{table}	**Significance**
33	97	106.22	1.5564	0.0000

3.3. Spatial Dependence Test

Spatial autocorrelation is performed to identify interregional relationships. Before testing, the initial step is to create a weighting matrix using the inverse distance approach. The selection of the inverse distance-based spatial weighting matrix is based on Tobler's First Law of Geography (Tobler, 1990), which states that adjacent locations have a stronger relationship than distant locations. In this approach, spatial weights are determined inversely with the distance between regions, so that spatial interactions weaken with increasing distance. Therefore, this approach is most suitable for representing the continuous diffusion of ICT development between provinces in Indonesia [22]. In a spatial context, the weighting matrix is determined by considering the actual distance traveled within an area, which is then normalized. The distance formula is written in equation (21):

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \tag{21}$$

where d_{ij} is the distance between locations i and j, u_i is the latitude of location i, v_i is the longitude of location i, u_j is the latitude of location j, v_j is the longitude of location j, and n is the total number of locations [23].

As an illustration, the spatial distance function is calculated in the following examples:

$$\begin{aligned}
d_{11} &= \sqrt{(4.6951 - 4.6951)^2 + (96.7494 - 96.7494)^2} = 0 \\
d_{12} &= \sqrt{(4.6951 - (-8.4095))^2 + (96.7494 - 115.1889)^2} = 22.6218 \\
&\vdots \\
d_{33,34} &= \sqrt{((-3.3194) - 2.1153)^2 + (103.9144 - 99.5451)^2} = 6.9733
\end{aligned}$$

After calculating the spatial distance, the relationship between regions is expressed formally in a matrix of size $n \times n$, where the element W_{ij} indicates the level of spatial relationship between locations i and j, as shown in equation (22):

$$W = W_{ij} = \begin{cases} 0, & i = j \\ \dfrac{(1/d_{ij})}{\sum_{k \neq i}^{n} (1/d_{ik})}, & i \neq j \end{cases} \tag{22}$$

Examples of calculations:

$$\begin{aligned}
W_{11} &= 0 \\
W_{12} &= \frac{(1/d_{ij})}{\sum_{k \neq i}^{n} (1/d_{ik})} = \frac{1/22.6218}{0.8164} = 0.0542 \\
&\vdots \\
W_{134} &= \frac{(1/d_{ij})}{\sum_{k \neq i}^{n} (1/d_{ik})} = \frac{1/6.9733}{0.8164} = 0.1756
\end{aligned}$$

The general form of the spatial weight matrix is as follows:

$$W = \begin{bmatrix} 0 & W_{12} & \cdots & W_{1,34} \\ W_{21} & 0 & \cdots & W_{2,34} \\ \vdots & \vdots & \ddots & \vdots \\ W_{34,1} & W_{34,2} & \cdots & 0 \end{bmatrix}.$$

After constructing the spatial weighting matrix, the next stage is to use Moran's I statistic to perform a spatial autocorrelation test in order to determine whether spatial dependency exists. The hypotheses for this test are formulated:

$$H_0 : I = 0 \quad \text{(no spatial autocorrelation)}$$
$$H_1 : I \neq 0 \quad \text{(spatial autocorrelation exists, positive or negative)}$$

The decision rule is to reject H_0 if $Z(I) > Z_{(1-\alpha)}$ or $Z(I) < -Z_{(1-\alpha)}$, otherwise if the $sig < \alpha$ [28]. The test statistic for Moran's I is given by equation (23):

$$Z(I) = \frac{I - E(I)}{\sqrt{\mathrm{Var}(I)}} \tag{23}$$

where

$$E(I) = -\frac{1}{n-1};$$
$$\mathrm{Var}(I) = \frac{n^2 S_1 - nS_2 + 3S_0^2}{(n^2-1)S_0^2};$$
$$S_1 = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(w_{ji}^* + w_{ij}^*)^2;$$
$$S_2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ji}^* + \sum_{j=1}^{n} w_{ij}^*\right)^2;$$
$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}^*$$

with w_{ij}^* denoting the standardized spatial weight.

Table 7. Moran's I Test Results

Period	**I**	**Z(I)**	**Significance**
2020	0.0629	2.4815	0.0065
2021	0.0555	2.2772	0.0114
2022	0.0527	2.2105	0.0135
2023	0.0415	1.9124	0.0279

Based on Table 7, for the 2020–2023 period, the expected value of Moran's I is $E(I) = -0.0303$ and the variance is $\mathrm{Var}(I) = 0.0014$. The results indicate a significant positive spatial autocorrelation at $\alpha = 5\%$. Although in 2023 the value did not meet the significance criterion in a two-tailed test with $Z_\alpha = 1.96$, it remained significant under a one-tailed test with $Z_\alpha = 1.645$. Overall, the spatial correlation pattern in the ICT-DI between provinces remains detectable, though with a tendency for its strength to weaken over the years.

3.4. Spatial Panel Model Examination

The Lagrange Multiplier (LM) test is utilized to identify the most suitable spatial regression model and to assess the presence of geographical dependence in the data. The statistical computation for the LM_{SAR} is presented in equation (5), along with the hypothesis formulation for the spatial lag model:

$$H_0 : \rho = 0 \quad \text{(no spatial lag)}$$
$$H_1 : \rho \neq 0 \quad \text{(spatial lag exists)}$$

If $sig < \alpha$ or $LM_{\text{SAR}} > \chi^2_{\alpha(1)}$, then H_0 is rejected. The weighting matrix is denoted by W, and the parameter estimate from the OLS regression model is denoted by β.

Meanwhile, the statistical form for the spatial error model or LM_{SEM} is presented in equation (6) with hypothesis test:

$$H_0 : \lambda = 0 \quad \text{(no spatial dependence of errors)}$$
$$H_1 : \lambda \neq 0 \quad \text{(spatial dependence of errors)}$$

Decision-making follows the rule of rejecting H_0 if $sig < \alpha$ or $LM_{\text{SEM}} > \chi^2_{\alpha(1)}$, indicating that the error term exhibits spatial dependence.

The Robust LM SAR (RLM-SAR) test is conducted to determine the presence of spatial lag dependence while controlling for potential spatial error dependence.

$$H_0 : \rho = 0 \quad \text{(SAR is not required)}$$
$$H_1 : \rho \neq 0 \quad \text{(SAR is required)}$$

For the RLM-SAR is rejected if $p < \alpha$ or $\text{RLM}_{\text{SAR}} > \chi^2_{\alpha,1}$, indicating spatial lag dependence.

Also robust LM SEM (RLM-SEM) to test for the presence of spatial error dependence while taking into account the possibility of spatial lag in the model.

$$H_0 : \lambda = 0 \quad \text{(SEM is not required)}$$
$$H_1 : \lambda \neq 0 \quad \text{(SEM is required)}$$

Where H_0 is rejected if the significance value is less than α or if the RLM-SEM statistic exceeds the critical value $\chi^2_{\alpha(1)}$, indicating the presence of spatial error dependence.
The LM calculation results are shown in the Table 8.

Table 8. Lagrange Multiplier (LM) Test Results

LM Test	χ^2_{count}	**Significance**	$\chi^2_{(0.05;1)}$
SAR-FE	42.605	0.0000	3.8415
SEM-FE	5.0742	0.0243	3.8415
RLM SAR-FE	40.471	0.0000	3.8415
RLM SEM-FE	2.9399	0.0864	3.8415

The LM test results in Table 8 show that both LM-SAR ($\chi^2_{\text{SAR}} = 42.605, \text{sig} = 0.0000$) and LM-SEM ($\chi^2_{\text{SEM}} = 5.0742, \text{sig} = 0.0243$) are significant since they exceed the critical value ($\chi^2_{\alpha}(1) = 3.8415$). However, the Robust tests indicate that only the Robust SAR-FE ($\chi^2_{\text{RLM SAR-FE}} = 40.471, \text{p-value} = 1.996 \times 10^{-10}$) remains significant, while the Robust SEM-FE ($\chi^2_{\text{RLM SEM-FE}} = 2.940, \text{p-value} = 0.0864$) is not significant. This suggests that a spatial lag model (SAR-FE) is more appropriate than a spatial error model (SEM-FE) for explaining the spatial dependence in ICT-DI across provinces.

The Spatial Autoregressive–Fixed Effect (SAR-FEM) model incorporates fixed effects to capture local characteristics. The dependent variable for each unit is influenced by both its internal factors at time t and the dependent variables of nearby units (spatial lag). The SAR-FE model estimation are shown in Table 9.

Table 9. SAR-FE Model Estimation Results

Variable	**Coefficient**	t_{count}	**Significance**	$t_{(0.05;1.9784)}$
X_1	-0.0005	-1.5562	0.1196	1.9784
X_2	0.0076	2.0519	0.0401	
X_3	-0.0454	-0.5734	0.5663	
X_4	0.0311	0.8330	0.4047	
X_5	0.0943	1.3549	0.1754	

According to Table 9, rejecting H_0 occurs if $|t_{\text{count}}| > t_{(0.05;1.9784)}$ or if $sig < 0.05$. It can be concluded that ICT-DI is significantly affected only by X_2 (coefficient $= 0.0076$, $t = 2.0519$, $sig = 0.0401$). Variable X_2 is spatially significant because denser areas tend to have more concentrated economic activity and ICT infrastructure, making the provision of digital services more efficient and spreading the impact to surrounding areas through inter regional interactions. Previous studies have also shown that agglomeration and spatial spillover effects play an important role in driving regional ICT development [24]. The remaining variables, X_1 ($sig = 0.1196$, $t = -0.0005$), X_3 ($sig = 0.5663$, $t = -0.0454$), X_4 ($sig = 0.4047$, $t = 0.0311$), and X_5 ($sig = 0.1754$, $t = 0.0943$), are not statistically significant. The insignificance of X_1 may reflect that demographic size alone does not robustly explain ICT-DI after accounting for spatial and structural heterogeneity, as demographic dividends interact with ICT adoption only when supported by human capital and economic conditions, for example, the relationship between demographics and ICT-DI varies depending on institutional and economic contexts [25]. Variable X_3 may not be significant because basic electricity access has become widespread in many regions, and studies have shown that, beyond basic access, electricity's contribution to ICT-DI outcomes depends on complementary infrastructure and socioeconomic conditions rather than access alone [26]. Similarly, X_4 does not show a significant effect in this model, consistent with findings that simple metrics of internet availability or usage are not always sufficient to capture the multifaceted contribution of ICT-DI to broader development outcomes without considering the quality, intensity, and context of use [27]. In FEM, variable X_4 has a positive and significant effect on ICT-DI. However, in the SAR-FE model, X_4 is no longer statistically significant. This change indicates that the effect of internet access has been partially internalized into the spatial lag component ($\rho W y$), so that a province's ICT-DI is influenced not only by internal internet usage, but also by the ICT-DI conditions in the surrounding region. Finally, X_5 may be statistically insignificant because mobile phone ownership has reached high levels globally, and recent analyses find that while mobile and broadband services contribute to development, their measurable effects vary significantly by development stage and context, highlighting that mere ownership does not guarantee broader ICT impacts in every setting[27].

The SAR-FE model explains approximately 98.47% of the variation in the ICT-DI ($R^2 = 0.9847$). The estimated SAR-FE equation is given as follows in equation (24):

$$y_{it} = 0.786 \sum_{j=1}^{34} w_{ij} y_{jt} - 0.0005X_{1it} + 0.0076X_{2it} - 0.0454X_{3it} + 0.0311X_{4it} + 0.0943X_{5it} + \mu_i + \varepsilon_{it} \quad (24)$$

The Spatial Error Model–Fixed Effect (SEM-FE) is a spatial panel model in which the response variable depends on internal factors of each unit i at time t, while the error terms exhibit spatial correlation. Fixed effects are included to capture local heterogeneity. The results are displayed in Table 10.

Table 10. SEM-FE Model Estimation Results

Variable	**Coefficient**	t_{count}	**Significance**	$t_{(0.05;1.9784)}$
X_1	-0.0009	-2.5131	0.0119	1.9784
X_2	0.0035	0.9401	0.3471	
X_3	-0.0067	1.7321	0.4909	
X_4	-0.0059	-0.6888	0.2173	
X_5	0.0144	-1.2336	0.8320	

Table 10 shows that only X_1 has a statistically significant negative impact on ICT-DI (coefficient $= -0.0009$, $t = -2.5131$, $sig = 0.0119$), indicating that an increase in X_1 tends to decrease ICT development. The other variables are not statistically significant since $sig > 0.05$ and $|t_{\text{count}}| < t_{(0.05;1.9784)}$.

The SEM-FE model explains approximately 92.92% of the variation in ICT-DI ($R^2 = 0.9292$). The estimated SEM-FE equation is expressed as follows in equation (25):

$$y_{it} = -0.0009X_{1it} + 0.0035X_{2it} - 0.0067X_{3it} - 0.0059X_{4it} + 0.0144X_{5it} + \mu_i + \phi_{it} \tag{25}$$

where,

$$\phi_{it} = 0.9164 \sum_{j=1}^{34} w_{ij} y_{jt} + \varepsilon_{it}$$

3.5. *Classic Assumptions*

Testing the classical assumptions aims to ensure that the regression model produces accurate and consistent estimates. Building a robust regression model requires verifying assumptions such as normality and homoscedasticity. The normality test results are displayed in Table 11.

Table 11. Normality Test Results

Test	**Statistic**	**Significance**
Lilliefors	0.0763	0.0510
Shapiro	0.9651	0.0015
Anderson	1.3368	0.0017
Cramer	0.2195	0.0029

The residual data in Table 11 are normally distributed since the Lilliefors test have a $sig > 0.05$, which lies outside the critical region (thus H_0 is accepted). Next, a heteroscedasticity test is performed using the Park test. This test applies the model in Equation (26):

$$\ln(e_i^2) = \ln(\beta_0) + \beta_1 \ln(X_{1i}) + \beta_2 \ln(X_{2i}) + \cdots + \beta_k \ln(X_{ki}) + \varepsilon_i, \quad i = 1, 2, 3, 4, 5. \tag{26}$$

where e_i^2 is the squared residual from the initial regression model, and ε_i is the error term in the Park test equation.

The hypotheses for the Park test are formulated as follows:

$$H_0 : \text{Var}(e_i) = \sigma^2, \quad i = 1, 2, 3, 4, 5 \qquad \text{(error variance is homoscedastic)}$$
$$H_1 : \text{Var}(e_i) \neq \sigma^2, \quad i = 1, 2, 3, 4, 5 \qquad \text{(error variance is heteroscedastic)}$$

Table 12. Heteroscedasticity Test Results (Park Test)

Variable	Coefficient	t_{count}	Significance
Intercept	-10.3723	-0.950	0.344
X_1	0.0866	0.289	0.773
X_2	0.1552	0.739	0.461
X_3	-1.2719	-0.358	0.721
X_4	0.2036	0.044	0.965
X_5	1.5522	0.393	0.695

Based on Table 12, the decision rule is to reject H_0 if the significance of the predictor variables are less than 0.05. Since all sig exceed 0.05, H_0 cannot be rejected. In light of this, it can be conclude that there are no heteroscedasticity problems in the regression model.

3.6. Model Evaluation and Spatial Effect

Model evaluation was performed by considering both the coefficient of determination R^2 (%) and MAPE (%). The best model was chosen using based on the highest R^2 and the lowest MAPE values. The evaluation results for the tested models are presented in Table 13.

Table 13. Best Model Evaluation Results

Model	R^2 (%)	MAPE (%)
Common Effect	15.482	7.9172
Fixed Effect	65.469	1.4119
Random Effect	53.101	1.8051
SAR-FE	98.472	1.1023
SEM-FE	92.929	2.6356

Based on Table 13, the SEM-FE achieved a relatively high R^2 value of 92.93%, but its MAPE was comparatively large (2.6356%). In contrast, the FEM explained 65.47% of the variation in the ICT-DI with a MAPE of 1.4119. Among all models, the SAR-FE yielded the most accurate estimation of ICT-DI, demonstrating the highest explanatory power ($R^2 = 98.472\%$) and the lowest prediction error (MAPE = 1.1023%).

Spatial effect analysis was conducted through the SAR-FE estimation to identify the spatial influence of the significant variable (X_2, population density) based on Table 13. The thematic results are visualized in Figure 2.

Figure 2. Effect of Population Density (X_2) on ICT-DI

Based on Table 9, population density (X_2) has a significant positive influence on the ICT-DI. Therefore, X_2 was further analyzed to evaluate its impact across provinces. Figure 2 shows the effect of population density (X_2) on ICT-DI in each province, based on the coefficient indicating the variation of the effect of X_2 from the SAR-FE model. The colours on the map indicate the magnitude of the influence of X_2 in each province, with positive effects appearing darker and negative effects appearing lighter. Based on Figure 2 Southeast Sulawesi experienced the largest increase in ICT-DI (approximately 6.19×10^{-6}), followed by North Sulawesi, West Sumatra, Jambi, Lampung, and Maluku, which also demonstrated smaller but positive changes. Conversely, Bangka Belitung recorded the largest decline (approximately -7.64×10^{-6}), followed by North Sumatra, Central Java, and West Kalimantan.

These findings indicate that regions with higher population density tend to achieve more advanced levels of ICT development. The greater demand for internet and communication services encourages providers to expand and improve infrastructure. According to [29], in densely populated areas, where faster networks and more affordable infrastructures are typically available, telecommunication providers generate higher revenue, there by promoting wider ICT adoption.

From a spatial perspective, the largest improvements occurred in Southeast Sulawesi, followed by North Sulawesi, West Sumatra, Jambi, Lampung, and Maluku. This pattern suggests that several provinces in Sulawesi and Sumatra have become relatively more progressive in ICT development. Conversely, provinces such as Bangka Belitung, North Sumatra, Central Java, and West Kalimantan exhibit stagnation or decline. Geographically, these areas face challenges related to uneven infrastructure investment, population distribution, and topographical constraints that hinder equitable network development.

Overall, the results reveal spatial disparities in ICT advancement across Indonesian provinces. Provinces with favorable demographic density or geographic accessibility demonstrate higher ICT performance, underscoring the need for region-specific digital inclusion strategies.

4. Conclusion

Considering the results and analysis, it was determined that the best estimation model was the SAR-FE with the highest R^2 value of 98.427 and the lowest MAPE value of 1.1023. The estimation model is as follows.

$$y_{it} = 0.786 \sum_{j=1}^{34} w_{ij} y_{jt} - 0.0005X_{1it} + 0.0076X_{2it} - 0.0454X_{3it} + 0.0311X_{4it} + 0.0943X_{5it} + \mu_i + \varepsilon_{it} \quad (27)$$

The spatial lag coefficient ($\rho = 0.786$) in the SAR-FE model shows a positive and strong inter-provincial dependence. In other words, an increase in ICT-DI in one province tends to drive an increase in ICT-DI in the surrounding region. This finding emphasises the importance of regional ICT development planning and coordination, so that provinces with high spillover effects can be used as centres for digital infrastructure and capacity development. In addition, the most significant positive factor affecting ICT-DI is population density, with a coefficient of 0.0076 and a significance of 0.0401. This suggests that as population density increases, ICT-DI also increases, with Southeast Sulawesi being the region most affected by this factor and Bangka Belitung being the region most negatively affected. Based on this analysis, solutions can be provided to design policies, for Southeast Sulawesi, as the region most positively affected by this factor, can capitalize on its population concentration by strengthening urban digital infrastructure, expanding ICT-based public services, and positioning dense districts as regional digital hubs that facilitate technology diffusion to surrounding areas. In contrast, Bangka Belitung, which is most negatively affected, requires targeted interventions such as improving inter-island digital connectivity, reducing infrastructure gaps caused by geographic fragmentation, and promoting inclusive digital access programs to prevent population dispersion from hindering ICT development.

5. Limitations

This study has several limitations. First, the spatial analysis only uses the Inverse Distance weight matrix. Second, the models used are limited to conventional panel methods (FEM, CEM, REM), as well as Spatial Panel, specifically the SAR-FE and SEM-FE models. For future research, it is recommended to consider the use of alternative weight matrices and more advanced methods, such as the Spatial Durbin Model (SDM), to obtain a more thorough knowledge of spatial impacts.

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