

DIGITAL WORKFORCE READINESS IN EAST JAVA: A SPATIAL ECONOMETRIC ANALYSIS USING THE GENERAL NESTING SPATIAL (GNS) MODEL, 2022–2024

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ABSTRACT

Regional disparities in digital infrastructure, labour-market characteristics, and socio-cultural environments create uneven digital workforce readiness across East Java. Understanding these disparities is essential for designing effective human-capital development strategies. This study examines the determinants of digital workforce readiness by analysing both local factors and spatial interactions between neighbouring regions. The analysis covers all districts and cities in East Java Province using regional data from 2022–2024. Workforce readiness is measured using the "Jobs" pillar of Indonesia's national digital readiness index (IMDI). The General Nesting Spatial (GNS) model is employed as the primary analytical approach to capture both direct effects and spatial spillovers of digital infrastructure, labour-market conditions, income, and cultural region characteristics. The results show that digital infrastructure is the most consistent local determinant, with positive and significant direct effects of 0.398 (2022), 0.366 (2023), and 0.108 (2024). Labor force participation shows a positive local effect of 0.327 in 2022, while its indirect spatial effect reaches -0.910 , indicating regional competition for skilled labour. Open unemployment produces a significant negative indirect effect of -1.184 in 2024, reflecting unemployment contagion across neighbouring districts. Per capita income shows a positive local effect of 3.339 in 2024, while cultural differences, particularly in the Madura region, show significant direct effects of 11.450 (2023) and 9.200 (2024). These findings demonstrate that digital workforce readiness in East Java is shaped by both structural local conditions and spatial dependencies between regions. This study highlights the importance of spatial econometric modelling in understanding regional digital readiness and provides evidence-based insights for developing equitable and culturally adaptive digital labour policies.

Keywords: East Java; spatial model; regional productivity; labour digitalisation

1. Introduction

The phenomena of globalization and the transition from Industry 4.0 to Industry 5.0 are driving technological upheavals, economic integration and changes in production and consumption patterns with great intensity and leading to a dizzying structural transformation (Angelova *et al.* 2021). Disruptions are occurring in all sectors, particularly in the labour market (Lim 2023). Automation, artificial intelligence and digitalization are steadily eroding traditional occupations while also producing new roles requiring different skills, thus making workers more competitive not only within regions but between countries of the global labour market (Abdussamad *et al.* 2022; Ozkan-Ozen & Kazancoglu 2021).

Labour competitiveness has thus become an increasing factor in region and national economic fortunes (Kouskoura *et al.* 2024). Regions blessed with high levels of skill and adaptability in their workers will improve their productivity and efficiency (Ozgen 2021). Human capital deficiencies will degrade the chances of economic transformation as industries

gear themselves to digitalization and automation. Competitiveness, the ability to produce goods and services that are acceptable in world markets while ensuring fair income and employment (Boikova *et al.* 2021), indicates a region's capacity to respond to the phenomena of globally-demanded goods/services and take advantage of opportunities by entering into commerce via digital means.

The global expansion of digital technology has quickened the pace of development of digital societies, where human and machine digital tools are embedded in daily lives and public services. Full-scale digitalization enhances efficiency, transparency, timeliness and relevance of services while changing labour market demands to digital literacy and flexibility and creativity (Berawi *et al.* 2020). Education and vocational training should embrace technology-driven industry needs, while government must substantiate development of inclusive digital ecosystems.

Indonesia, as a developing country, faces ongoing challenges in preparing a workforce capable of adapting to rapid digital development. Although digital usage is increasing, there are still gaps in digital competency, including critical thinking, innovation, and collaboration. Regional variations in access to digital education and vocational training exacerbate gaps in human capital preparation. Developing flexible and competitive human resources is thus critical for maintaining an inclusive digital economy.

These national priorities are consistent with the Third Asta Cita of Prabowo Subianto and Gibran Rakabuming Raka (President and Vice President of the Republic of Indonesia), which emphasizes the importance of quality jobs, entrepreneurship, creative industries, and infrastructure development. This agenda is congruent with SDG 8, which calls for equitable and sustainable economic growth and productive employment for all (Bilek-Steindl *et al.* 2022).

One of Indonesia's main economic contributors, East Java, has the strategic potential to boost national growth through improved human capital. The province, which depends on trade, manufacturing, and agriculture, needs workers who are creative and tech-savvy. East Java is ranked third nationally in the East Ventures–Digital Competitiveness Index (EV-DCI) 2024, which is an improvement over 2023 ("East Ventures – Digital Competitiveness Index 2024," 2024). This indicates notable advancements in digital infrastructure, technology utilization, and digital human resource development. However, specific policy interventions are still required to guarantee industry-based training and fair development of digital skills across districts.

The opportunities and difficulties of Indonesia's digital transition are highlighted in earlier research. According to Agustina *et al.* (2023), skill mismatches, unfair job distribution, and restricted access to training are the main causes of unemployment. The significance of digital literacy techniques in lowering the hazards associated with false information and uneven access to information is emphasized by Fitria *et al.* (2022). These results highlight the possibilities and difficulties of digital transformation.

Spatial disparities also persist within East Java. According to Koswara (2024), cities such as Surabaya, Sidoarjo, and Malang progress more rapidly in digital access and training than regions like Madura, Tapal Kuda, and the highlands. Such inequalities suggest heterogeneous levels of digital readiness and potential spatial spillover effects. Research shows that economic spillovers among East Java districts are bidirectional, with spread effects dominating backwash effects (Sari & Wahed 2023). Studies in Kalimantan reveal that growth centres can generate positive or negative spillovers depending on output, labour, and investment.

Given these conditions, spatial modelling offers a robust approach to mapping digital readiness more accurately. Mathematical modelling provides a systematic framework for representing complex real-world dynamics and examining interactions among factors that influence observed outcomes (Yunus *et al.* 2021). Incorporating spatial dependence makes it

possible to analyze variations in digital infrastructure, digital literacy, and technology integration across regions, as captured by the Indonesian Digital Society Index (IMDI). The majority of earlier research concentrates on digital literacy, unemployment, or labor competitiveness alone and never takes into account the spatial interconnectedness between regions, despite the expanding body of literature on digital transformation and labor-market preparation in Indonesia. A thorough spatial econometric approach that concurrently incorporates local impacts, neighborhood spillovers, and spatial error dependence has been used in a small number of studies to analyze digital workforce readiness. This leads to a significant study gap, especially when it comes to comprehending how regional differences in digital infrastructure and labor market conditions interact with one another across adjacent districts. This study fills that gap by combining the General Nesting Spatial (GNS) model with the IMDI, namely the Jobs pillar, for all East Javan districts and cities in 2022–2024. Unlike conventional regression approaches, Ordinary Least Squares (OLS) is employed only as a baseline diagnostic model. At the same time, GNS serves as the primary analytical framework to estimate both direct and indirect spatial effects. This approach provides a more comprehensive understanding of how digital infrastructure, labour-market conditions, and cultural regional differences shape workforce readiness in the digital economy.

This study, therefore, examines digital readiness and workforce preparedness in East Java using IMDI data from 2022 to 2024. Specifically, it investigates the determinants of digital readiness, identifies spatial spillover effects, and evaluates the consistency of these effects across years. The findings aim to provide evidence-based insights for East Java's local government in formulating strategies to strengthen digital readiness and develop a competitive, innovative, and productive digital workforce ecosystem.

2. Conceptual Framework and Methodology

2.1. Conceptual Framework

2.1.1. Concept of workforce quality

The ability of an individual to carry out duties effectively, efficiently, and adaptably in response to the ever-changing needs of the labor market is reflected in the quality of the workforce. Indicators, including educational attainment, technical abilities, work experience, health status, and preparedness to adapt to technological change, are frequently used to evaluate it. The degree to which employees can contribute to production processes and more general economic goals in an optimal manner is captured by these measures. Strengthening core competencies, technical (hard) skills, non-technical (soft) skills, and digital literacy is necessary to create a workforce of the highest caliber (Safrankova *et al.* 2020). The ability of an individual to carry out duties effectively, efficiently, and adaptably in response to the ever-changing needs of the labor market is reflected in the quality of the workforce. Indicators, including educational attainment, technical abilities, work experience, health status, and preparedness to adapt to technological change, are frequently used to evaluate it. The degree to which employees can contribute to production processes and more general economic goals in an optimal manner is captured by these measures. Strengthening core competencies, technical (hard) skills, non-technical (soft) skills, and digital literacy is necessary to create a workforce of the highest caliber (Safrankova *et al.* 2020).

At the organizational and regional levels, high labor quality is strongly associated with increased productivity and potential for innovation. Workers with the necessary skills and adaptability can increase production efficiency, speed up the adoption of new technologies, and

produce innovative, value-added solutions. Over time, this promotes equitable and sustainable economic growth and increases competitiveness. Therefore, for areas looking to prosper in the face of swift global economic change, investing in worker quality (via education, training, and the creation of digital ecosystems) is a strategic priority (Kassa & Worku 2025; Liang *et al.* 2025).

2.1.2. *Human capital theory*

According to Gary Becker's original Human Capital Theory, people can increase their output by making investments in their health, education, training, and job experience (Becker 1975). According to Becker (1975), human resources should be viewed as a type of capital that can be enhanced through skill and capability development, just like physical capital. Training and education are seen as long-term investments that pay off in the form of increased economic activity and individual profits. According to this viewpoint, investments made to enhance human capital are strategic investments that have the potential to improve both individual and societal welfare (Saleh 2020).

The foundation of the theory's application is the connection between investments in human capital and economic growth. Increased productivity, innovation, and efficiency are all possible in economic systems with a higher-quality workforce. A more competent, adaptable, and competitive labor force is typically produced in areas that devote resources to improving public health, education, and vocational training (Babacan 2022; Pawar & Babacan 2025). In turn, these advancements increase employment possibilities, lessen interregional inequities, and foster regional economic growth. Therefore, human capital formation-focused regional development plans are a useful tactic for promoting equitable and long-term economic growth.

2.1.3. *Concept of the digital economy*

The creation, distribution, and consumption of goods and services carried out via digital platforms are all included in the term "digital economy," which encompasses all economic activities that depend on digital technologies and the internet. Data, information, and technology are essential resources in the digital economy that promote productivity, openness, and creativity in a variety of industries (Kumar *et al.* 2025). The information and communication technology (ICT) industry, e-commerce, application-based services, and the application of big data, artificial intelligence, and the Internet of Things (IoT) in economic processes are all included in this concept. Significant changes in the way economic players interact are made possible by the growth of the digital economy, which both challenges established business models and creates new opportunities (Javaid *et al.* 2022; Suntsova 2024).

Digital infrastructure, which includes data centers, cybersecurity systems, and high-speed internet networks, is a crucial component of the digital economy. Connectivity, information access, and effective real-time data interchange are all supported by a strong digital infrastructure (Aleca & Mihai 2025; Xia & Md Johar 2025). The successful operation of digital-based economic activities, including e-commerce, digital financial services, and smart logistics systems, is made possible by dependable internet networks. Furthermore, data centers are crucial for processing, storing, and managing vast amounts of information, all of which are necessary for making data-driven decisions. Cybersecurity technologies are equally important since they guarantee user confidence in digital platforms by shielding financial transactions and personal information from online threats. Without adequate digital infrastructure, the advancement of the digital economy can be hindered and may widen disparities between regions that are digitally connected and those with limited technological access.

2.1.4. Digital economy theory

The structure, speed, and direction of contemporary economic growth have been altered by the thorough integration of digital technologies into economic activity, as explained by the theory of the "digital economy." In addition to altering the production and distribution of products and services, digital transformation also affects market efficiency, current business models, and the connections between economic actors. Process automation, data-driven decision-making, and the generation of new economic value that would not be possible in traditional economic systems are made possible by technologies like cloud computing, artificial intelligence, big data, and the Internet of Things (IoT) (Javaid *et al.* 2022; Vărzaru & Bocean 2024). These shifts contribute to changes in economic structure, including the movement of value added from traditional sectors toward technology-based sectors, the emergence of new platform-based economies, and the diminishing role of conventional intermediaries due to service digitalization.

Workforce competencies must alter significantly as a result of these changes. According to the theory of the digital economy, workers must possess critical abilities such as technical literacy, adaptability, and data management and utilization skills in order to stay relevant. Because digitalization directly impacts the need for a variety of skills, speeds up the shift from routine tasks to analytical and creative roles, and emphasizes the necessity of lifelong learning to keep up with technological advancements, this theory has significant relevance for the workforce.

At the regional level, such as in East Java Province, the application of digital economy theory can be observed in how local governments, businesses, and educational institutions respond to digital transformation. This response includes expanding ICT infrastructure, improving digital literacy among communities, and fostering an inclusive innovation ecosystem. These efforts not only enhance regional competitiveness but also prepare a workforce capable of contributing effectively to a rapidly evolving digital economy.

2.2. Research Methodology

2.2.1. Spatial econometric foundation

"Everything is related to everything else, but near things are more related than distant things," according to Tobler's First Law of Geography (Tobler 1970). According to this theory, the probability of interaction or reliance between locations grows with spatial proximity. In actuality, spatial phenomena like disease transmission, economic activity, and population mobility are typically more closely correlated in nearby locations than in farther-flung ones. In econometrics, spatial proximity reflects the extent to which observations from nearby locations influence one another (Kelejian & Piras 2017).

One of the most widely used tools to represent spatial relationships is the contiguity matrix, denoted by $\mathbf{C}$, whose elements are c_{ij} :

$$\mathbf{C} = \begin{pmatrix} c_{11} & c_{12} & \cdots & c_{1N} \\ c_{21} & c_{22} & \cdots & c_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ c_{N1} & c_{N2} & \cdots & c_{NN} \end{pmatrix} \quad (1)$$

Each row i and column j correspond to spatial units, and the elements take the form:

$$c_{ij} = \begin{cases} 1; & \text{if locations } i \text{ and } j \text{ are adjacent} \\ 0; & \text{otherwise} \end{cases} \quad (2)$$

According to the Queen Contiguity criterion, two areas are deemed adjacent if they share a vertex or a boundary. The contiguity matrix is row-normalized to produce the standardized spatial weight matrix $\mathbf{W}$:

$$\mathbf{W} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{22} & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & w_{NN} \end{pmatrix} = \begin{pmatrix} \frac{c_{11}}{c_{1\cdot}} & \frac{c_{12}}{c_{1\cdot}} & \cdots & \frac{c_{1N}}{c_{1\cdot}} \\ \frac{c_{21}}{c_{2\cdot}} & \frac{c_{22}}{c_{2\cdot}} & \cdots & \frac{c_{2N}}{c_{2\cdot}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{c_{N1}}{c_{N\cdot}} & \frac{c_{N2}}{c_{N\cdot}} & \cdots & \frac{c_{NN}}{c_{N\cdot}} \end{pmatrix} \quad (3)$$

where $c_{i\cdot} = \sum_{j=1}^N c_{ij}$.

2.2.2. Detection of spatial autocorrelation

Spatial autocorrelation refers to the dependence of a variable's value at one location on the values of neighbouring locations. When spatial dependence exists but is ignored, OLS estimators become inefficient (Fornango 2010). To detect spatial autocorrelation, Moran's I statistic is used, with hypotheses:

$$\begin{aligned} H_0 &: \forall \text{Cor}(Z_i, Z_j) = 0; i \neq j \text{ vs} \\ H_1 &: \exists \text{Cor}(Z_i, Z_j) \neq 0; i \neq j \end{aligned}$$

Moran's I is computed as:

$$I = \frac{\sum_{j=1}^n \sum_{i=1}^n w_{ij} (Z_i - \bar{Z})(Z_j - \bar{Z})}{\sum_{i=1}^n (Z_i - \bar{Z})^2} \quad (4)$$

Moran's I values close to zero imply a random spatial pattern, a negative value denotes spatial dispersion, and a positive value suggests clustering.

To further determine the appropriate spatial model, the Lagrange Multiplier (LM) tests are used, consisting of LM-lag and LM-error (Anselin *et al.* 2013). LM-lag detects dependence in the dependent variable, whereas LM-error identifies spatial dependence occurring through the error structure.

2.2.3. General Nesting Spatial (GNS) Model

The GNS model, which simultaneously integrates spatial lag, geographically lagged predictors, and spatial error processes, provides the most complete specification among the several spatial regression techniques. The general form of the GNS model can be written as follows:

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \boldsymbol{\theta} \mathbf{W} \mathbf{X} + \mathbf{X} \boldsymbol{\beta} + \mathbf{u} \quad (5)$$

$$\mathbf{u} = \lambda \mathbf{W} \mathbf{u} + \boldsymbol{\varepsilon} \quad (6)$$

where $\mathbf{y}$ is the response variable vector, $\mathbf{X}$ is the matrix of predictor variables, $\mathbf{W}$ is the spatial weight matrix, ρ is the spatial lag coefficient for the response variable, $\boldsymbol{\theta}$ is the coefficient for the spatial lag of the predictor variables, λ is the spatial error coefficient (spatial error dependence), $\mathbf{u}$ is the error component, and $\boldsymbol{\varepsilon}$ is the random error vector. Both LM-lag and LM-

error were statistically significant in preliminary diagnostic testing using LM tests, showing the simultaneous presence of spatial lag dependence and spatial error dependency. Simpler models like the Spatial Error Model (SEM), which only takes into account spatial error correlation, or the Spatial Autoregressive (SAR) model, which only incorporates lag dependency, would not be adequate to accurately depict the spatial structure of the data in such circumstances. The GNS model is therefore more appropriate because it simultaneously incorporates spatial lag of the dependent variable, spatially lagged explanatory variables, and spatial error processes within a single unified framework. This allows a more comprehensive estimation of both direct local effects and indirect spillover effects across neighbouring regions.

2.2.4. Spillover effects in GNS

In the context of the GNS model, spillover effects occur when changes in an independent variable at one location influence outcomes in neighbouring locations (Elhorst 2022). Spillovers arise through both spatial lag dependence and spatially lagged predictors. The total marginal effects are calculated as:

$$\frac{\partial \mathbf{Y}}{\partial \mathbf{X}} = (\mathbf{I} - \rho \mathbf{W})^{-1}(\boldsymbol{\beta} + \boldsymbol{\theta} \mathbf{W}) \quad (7)$$

The spillover effect, $\partial \mathbf{Y} / \partial \mathbf{X}$, is an $(n \times k)$ matrix in which the diagonal elements represent the direct effects, while the off-diagonal elements represent the indirect effects.

2.2.5. Data

This analysis makes use of annual regional statistics for all 38 districts and cities in Indonesia's East Java Province from 2022 to 2024. Regencies and municipalities that are monitored every year serve as the unit of analysis, leading to recurring annual regional observations. The Jobs pillar of the IMDI, which gauges labor preparedness for digital transformation, is the main source of data. Digital infrastructure, labor force participation rate, open unemployment rate, and average per capita income were among the other explanatory variables that were gathered from relevant government reports and official regional statistical publications released by Badan Pusat Statistik (BPS). The GNS model is used to estimate annual cross-sectional regional observations for each year in order to incorporate potential temporal fluctuations in spatial dependence. The primary response variable is the Jobs pillar of the IMDI, measured as an index score representing workforce readiness in digital transformation, particularly in terms of labour participation and technology-based work skills.

The Jobs pillar is modelled as a function of several predictor variables:

1. Infrastructure (Infra) – measured using the Digital Infrastructure Index (index score, unitless), representing the availability and accessibility of digital infrastructure such as internet networks, ICT devices, and other supporting services.
2. Labor Force Participation Rate (Labor) – measured as a percentage (%), indicating the extent to which the working-age population actively participates in the labour market.
3. Open Unemployment Rate (Unemp) – measured as a percentage (%), capturing the mismatch between labour supply and labour demand within a region.
4. Average Income per Capita (lnInc) – originally measured in Indonesian Rupiah (IDR) and transformed into natural logarithm form to reduce scale differences and improve model stability, serving as an indicator of economic welfare and the population's ability to access digital services.

5. Cultural Region (Reg) – represented as a binary dummy variable reflecting socio-cultural regional classifications, including variations in social norms, communication patterns, and technological adaptability.

The classification of cultural regions in East Java is presented in Figure 1.

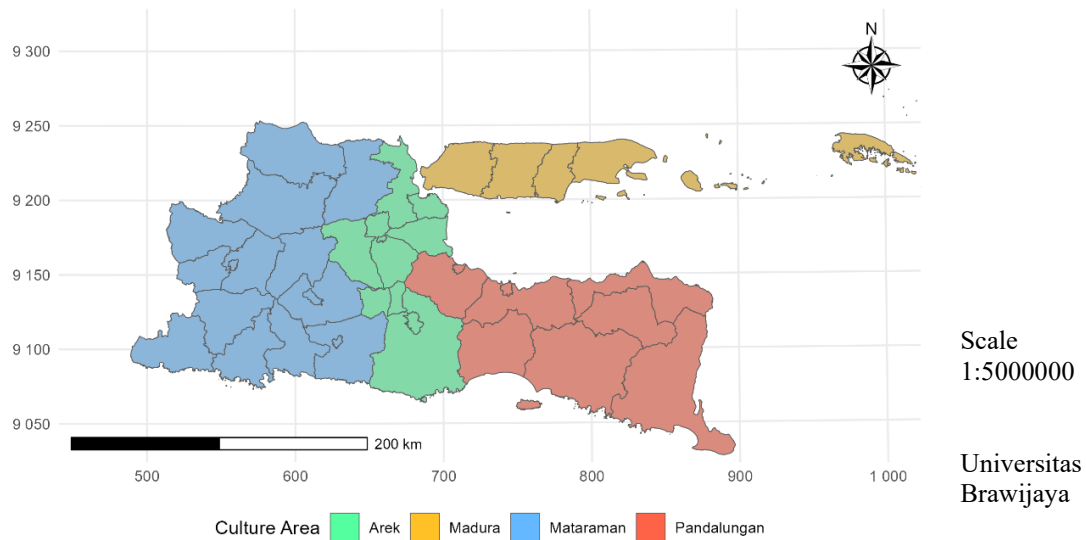


Figure 1: Classification of cultural regions in East Java

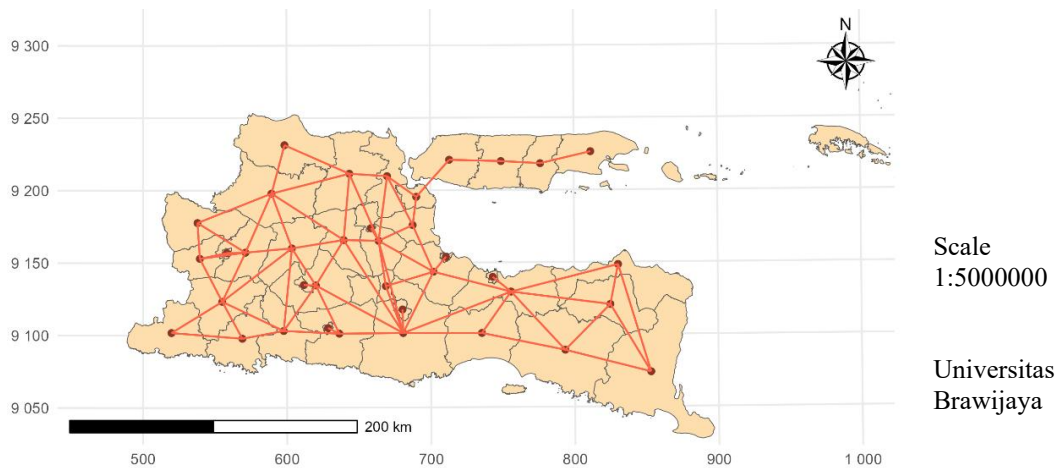


Figure 2: Illustration of the adjacency matrix Queen Contiguity

As shown in Figure 2, a Queen Contiguity spatial weight matrix was used to quantify the spatial effect. However, in order to account for the physical circumstances and strategic infrastructure of the area, a modification of the standard concept of contiguity was established throughout its implementation. In particular, because of the Suramadu Bridge, the City of Surabaya and Bangkalan Regency were regarded as neighboring entities in the spatial matrix,

even if they did not share an administrative border by side or corner. The weighting scheme's premise of spatial interaction is justified by this infrastructure's direct physical connectivity between the two areas.

The spatial modelling procedure using the GNS specification was conducted through the following steps:

1. **Exploratory spatial data analysis** was performed to identify the presence of spatial autocorrelation using Moran's I test.
2. **Estimation of the GNS model parameters** initially using OLS as a baseline approach. To validate the estimation results, residual diagnostics were performed, including tests for normality using the Shapiro-Wilk Test and the homogeneity of residual variance test by the Breusch-Pagan method.
3. **Model evaluation**, which included assessing parameter significance, examining goodness-of-fit metrics, and conducting LM tests to determine the dominant form of spatial dependence.
4. **Interpretation of results**, focusing not only on the direct effects but also on the spillover effects that capture how changes in one region influence outcomes in neighbouring regions.

3. Results and Discussion

The descriptive statistics for the primary research variables employed in this study are shown in **Table 1**. The Jobs index, which measures preparedness for the digital workforce, has an average value of 38.45 with a standard deviation of 7.41, suggesting that East Javan districts and cities vary moderately. Regional differences in workforce preparation are still significant, as evidenced by the first quartile (31.50) and third quartile (43.76).

Table 1: Descriptive statistics analysis

Variable	Mean	Q1	Median	Q3	St.Dev
Jobs	38.45	31.50	38.15	43.76	7.41
Infra	56.72	45.86	60.74	63.04	9.79
Labor	72.70	70.14	72.35	74.68	3.78
Unemp	4.66	3.79	4.63	5.48	1.55
Inc	1,266,571.62	1,002,751.68	1,149,074.50	1,526,485.85	374,757.93

With a mean score of 56.72 and a very high standard deviation of 9.79, digital infrastructure (Infra) indicates significant regional variations in infrastructure accessibility and availability. With a lower standard deviation of 3.78 and a comparatively high and consistent average of 72.70%, labor force participation (Labor) is more evenly distributed between districts.

With a moderate dispersion and an average of 4.66%, open unemployment (Unemp) reflects regional variations in labor-market absorption. With a mean of IDR 1,266,571.62 and a standard deviation of IDR 374,757.93, average income per capita (Inc) has the greatest variability, suggesting considerable economic disparity between districts and cities. These descriptive findings support the use of spatial econometric analysis and offer preliminary evidence that regional differences in digital infrastructure, labor-market conditions, and economic welfare may contribute to variations in digital workforce readiness.

This study's first modeling phase used the OLS method for multiple linear regression. The purpose of the model was to calculate how the independent variables, Infra, Labor, Unemp, Inc., and Reg, affect the dependent variable, Jobs. Following model estimation, a number of diagnostic tests were performed to assess the traditional OLS assumptions. These tests included the Shapiro-Wilk test for residual normality, the Breusch-Pagan test for homoscedasticity, and

Moran's I for residual spatial autocorrelation, which was used to determine whether residuals showed spatial correlation across regions. OLS is no longer an effective or impartial estimator if Moran's I is statistically significant, indicating the presence of spatial autocorrelation.

Table 2: Diagnostic results of the classical assumption tests

Tests	Statistic Test	p-value
Normality (Shapiro-Wilk)	0.971	0.432
Homogeneity of Variance (Breusch-Pagan)	6.734	0.457
Spatial Autocorrelation (Moran's I)	2.502	0.006

The residuals are normally distributed, according to the Shapiro-Wilk test, which produces a p-value of 0.432. The Breusch-Pagan test yields a p-value of 0.457, indicating that heteroskedasticity is absent and the residual variance is uniform. On the other hand, Moran's I statistic yields a p-value of 0.006, indicating that the OLS residuals exhibit significant spatial autocorrelation. This result demonstrates that the OLS model's spatial dependence breaks the independence assumption.

Further testing was done to determine the most suitable type of spatial dependency, that is, whether it results from spatial lag dependence or spatial error dependence, after significant spatial autocorrelation was found in the residuals. The LM tests were used for this evaluation. The LM tests provide information on the dominant type of spatial dependence present in the model.

Table 3: Spatial dependence component tests

Component	Statistic Test of LM	p-value
Lag	4.538	0.033
Error	4.862	0.027

Table 3 displays the outcomes of the spatial dependence component tests conducted using the LM methods. Both the LM-lag and LM-error tests produce statistically significant p-values at the 5% level, according to the results. The LM-lag test generates a p-value of 0.033, but the LM-error test yields a p-value of 0.027. These findings imply that the model's lag and error mechanisms cause spatial dependency to develop concurrently. Because it integrates spatial lag, spatial inaccuracy, and spatially autocorrelated disturbances into a single, cohesive system, the GNS model is the most suitable spatial modeling technique.

To account for simultaneous spatial dependence, the GNS model was utilized. Rather than estimating a single pooled model, the GNS specification was applied separately for each year within the observation period (2022, 2023, and 2024) to capture potential variations in spatial mechanisms across time. The estimated coefficients and their statistical significance are presented in Table 4.

Based on the parameter estimates in Table 4, the GNS model reveals substantial year-to-year variation in both the direct (local) and indirect (spatial) effects of the explanatory variables. The spatial dependence component, captured through the spatial lag parameter (ρ), indicates that the level of workforce digital readiness in a given district is influenced by conditions in neighbouring districts, reinforcing the importance of accounting for spatial interactions in regional labour-market dynamics.

Table 4: Estimation and statistical significance of the GNS model

	Year		
	2022	2023	2024
Local Effect (Direct)			
(Intercept)	-52.791 (91.647)	-37.970 (31.451)	15.911 (37.576)
<i>Infra</i>	0.398 (0.149) **	0.366 (0.063) ***	0.108 (0.045) *
<i>Labor</i>	0.327 (0.178) +	-0.008 (0.056)	0.147 (0.102)
<i>Unemp</i>	0.343 (0.536)	-0.432 (0.199) *	0.333 (0.276)
<i>lnInc</i>	1.389 (2.418)	0.501 (0.834)	3.339 (1.099) **
Reg (ref: Arek)			
Madura	5.060 (7.233)	11.450 (3.230) ***	9.200 (3.079) **
Mataraman	2.032 (2.520)	-1.493 (0.906) +	-0.610 (0.813)
Pandalungan	-7.141 (3.121) *	1.618 (1.093)	0.672 (0.943)
Spatial Effect (Indirect)			
(Intercept)	-0.28 (0.390)	-0.222 (0.185)	-0.203 (0.130)
<i>Infra</i>	-0.910 (0.387) *	-0.103 (0.109)	-0.342 (0.182) +
<i>Labor</i>	-0.936 (0.817)	-0.065 (0.327)	-1.184 (0.372) **
<i>Unemp</i>	6.634 (5.128)	3.584 (2.206)	-0.966 (2.087)
<i>lnInc</i>			
Reg (ref: Arek)	0.562 (7.938)	-12.872 (3.092) ***	-11.354 (3.368) ***
Madura	4.985 (3.530)	1.79 (1.215)	1.336 (1.007)
Mataraman	14.524 (4.102) ***	-2.090 (1.629)	-1.439 (1.119)
Component of Spatial Dependency			
(lag)	0.492 (0.287) +	0.415 (0.245) +	0.334 (0.541)
(error)	-0.140 (0.408)	-0.342 (0.332)	0.292 (0.583)
Goodness-of-Fit			
AIC	216.8	136.4	135
BIC	246.3	165.9	164.5
RMSE	2.51	0.87	0.87

Notes: (+) significance at 0.1; (*) significance at 0.05;
 (**) significance at 0.01; (***) significance at 0.001

The degree to which workforce digital readiness in one area is impacted by the readiness levels of nearby districts is indicated by the spatial lag parameter (ρ). Although only marginally significant, the positive values of ρ in 2022 (0.492) and 2023 (0.415) indicate that areas with higher levels of preparedness for the digital workforce are typically surrounded by areas with comparable preparation. This shows that there is an interregional connection through shared access to digital opportunities, information sharing, and labor mobility. However, the decreasing amplitude and insignificance of ρ non 2024 suggest that this endogenous spatial

reliance weakened over time, perhaps as a result of the development of the digital workforce becoming more dependent on local structural factors rather than direct neighbor impact.

The spatial error parameter (λ) captures unobserved spatial dependence arising from omitted regional characteristics that are geographically correlated, such as institutional quality, local governance, or informal labour-market networks. Although λ is not statistically significant across the three years, its presence suggests that some unobserved regional factors may still influence workforce readiness indirectly. This result suggests that observed explanatory variables and spillover effects, rather than residual spatial correlation alone, provide a better explanation for the majority of spatial dependence in this investigation.

The indirect consequences further support the significance of spillover mechanisms. Regional competition for skilled workers is suggested by the considerable negative indirect effect of labor participation, where labor concentration in one area may lower workforce readiness in neighboring districts. In a similar vein, the negative spillover effect of unemployment suggests a contagion effect, whereby high unemployment in one location reduces the resilience of the labor market in other areas. On the other hand, the negligible spatial spillover of digital infrastructure suggests that advancements in digital facilities and internet connectivity typically produce localized advantages rather than widespread interregional dispersion.

In all three years, the local impact of digital infrastructure (Infra) is statistically significant and continuously demonstrates a favorable correlation with workforce readiness. This finding implies that a region's capacity to train its labor force for digital transformation is still significantly influenced by the availability and accessibility of digital infrastructure. Higher preparedness levels are typically found in areas with greater infrastructure. However, the spatial effect of Infra is not statistically significant, suggesting that gains in one district's infrastructure do not necessarily transfer to nearby districts.

In contrast to its spatial impacts, which exhibit a negative and statistically significant coefficient in 2022 and a marginally significant one in 2024, the local effect of labor force participation (Labor) is only significant in 2022. This pattern suggests that while increased local labor participation improves digital readiness within the same district, it may also put nearby areas under competitive pressure, a phenomenon known as the "spatial crowding effect." These dynamics are consistent with reported labor mobility patterns in East Java, where people from Madura and rural hinterlands frequently relocate to Surabaya and neighboring urban centers in search of better job opportunities.

Only in 2023 does unemployment (Unemp) show a notable negative local effect, which is in line with the hypothesis that increased unemployment impairs digital readiness. More notably, in 2024, the spatial effect of unemployment turns considerably negative, suggesting a contagion-like spillover: high unemployment in one district can lower labor readiness in other areas. According to Gunawan and Nuzula (2020) and Soinbala and Bektı (2023), structural unemployment in one area might jeopardize the region's overall digital preparedness, highlighting the interrelated labor-market pressures across districts.

Per capita income (lnInc) shows a significant and positive local effect only in 2024, suggesting that higher-income districts have a stronger capacity to equip their workforce with digital competencies through improved access to education, online training, and digital tools. The absence of significant spatial effects implies that income-driven benefits tend to be localized, without automatically spreading to adjacent areas. This finding corresponds with prior evidence that economic growth is geographically "sticky" and does not diffuse evenly across regions (Aspiansyah & Damayanti 2019).

The findings also show that different cultural regions have varied effects, especially between Madura and Arek. Consistent differences are seen in both the direct and indirect impacts, indicating that workforce preparation outcomes are significantly influenced by regional differences in cultural values, migration inclinations, and access to digital education. Over the course of the three years, there are no statistically significant differences between Arek and the other cultural clusters (Mataraman and Pandalungan). These results highlight how important it is to create labor-development plans that take socio-regional and cultural settings into account.

Findings from cross-national studies, which emphasize the critical significance of spatial dimensions in explaining variations in labor productivity and digital readiness, are supported by the general pattern of results. For instance, studies on labor productivity in Russia show that regional workforce dynamics are greatly impacted by geographical dependence, necessitating measures tailored to individual regions (Larionova & Varlamova 2020). Evidence from the Perm region also demonstrates geographical variation in digital labor demand and unemployment as a result of unequal digitalization (Dubrovskaya & Kozonogova 2021), suggesting dynamics similar to those seen in East Java.

Taken together, the GNS estimates from 2022–2024 reveal that digital workforce readiness in East Java is shaped by a combination of local socioeconomic attributes and spatial interactions between districts. The significance of the spatial lag parameter (ρ) underscores that workforce, information, and technology flows extend beyond administrative boundaries. Digital infrastructure emerges as the most consistently influential local driver, supporting its role as a foundational structural prerequisite for digital transformation (Kabir 2021; Koswara 2024). Meanwhile, spatial contagion in unemployment and competitive labor-market interactions highlight the need for coordinated, cross-district policy interventions.

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), two goodness-of-fit metrics, offer more proof of the GNS model's suitability over the course of the three observation years. The findings demonstrate that from 2022 (AIC = 216.8; BIC = 246.3) to 2023 (AIC = 136.4; BIC = 165.9) and 2024 (AIC = 135.0; BIC = 164.5), both AIC and BIC values significantly decline. After taking model complexity into consideration, lower AIC and BIC values show improved model fit and stronger explanatory performance. As the structural relationship between digital infrastructure, labor market conditions, and workforce preparedness grows more consistent over time, this suggests that the GNS model offers a more solid portrayal of the digital workforce ready in the coming years. In addition, the lower RMSE values in 2023 and 2024 (0.87) compared to 2022 (2.51) further support the improved predictive accuracy of the model.

The estimated coefficients of the spatial lag parameter (ρ) and spatial error parameter (λ) were not consistently significant across the observation years, despite the LM tests showing the existence of both spatial lag and spatial error dependence. This implies that spatial dependence in digital workforce readiness may function more through particular spillover channels represented by the spatially lagged explanatory variables (**WX**), such as labor participation, unemployment, and cultural region characteristics, than through strong endogenous interaction of the dependent variable or through spatially correlated disturbances. In the context of East Java, digital infrastructure development tends to be localized within each district, where improvements in internet access, digital facilities, and training programs mainly benefit the same region without generating substantial diffusion to neighbouring areas. This finding is consistent with Aspiansyah and Damayanti (2019), who found that regional economic growth in Indonesia often remains geographically concentrated, and with Dubrovskaya and Kozonogova (2021), who reported that digital labor demand and workforce adaptation are strongly influenced by local structural conditions rather than uniform regional spillovers.

Finally, the evidence relating to cultural regions (particularly Madura and Arek) further underlines that spatial policies must be integrated with cultural and social considerations to develop digital-ready human capital effectively.

4. Conclusion

One strategic element that influences the success of regional economic transformation is the workforce's preparedness for the digital age. East Java's digital workforce readiness is impacted by both local and spatial factors, according to the GNS model estimation results for 2022–2024. A more prepared workforce is typically found in areas with greater access to and quality of digital infrastructure, as evidenced by the consistent positive and considerable local effect of digital infrastructure. Its geographic effect is still negligible, though, indicating that improvements in one area do not always have a positive knock-on effect on other places.

Although labor force participation has a beneficial local impact, regional rivalry for skilled workers and employment prospects may result in negative geographical impacts. In the meantime, unemployment has a detrimental impact both locally and geographically, suggesting the existence of a contagion effect whereby high unemployment in one area impairs digital preparedness in nearby areas. While per capita income does not result in cross-regional externalities, it does have a favorable local impact. Furthermore, cultural heterogeneity, specifically, the distinctions between the Arek and Madura cultural regions, plays a significant role, suggesting that social norms and cultural traits influence the workforce's ability to adapt to digital transition.

These findings confirm that digital workforce readiness in East Java, Indonesia, depends not only on internal regional conditions but also on interactions between neighbouring areas. Future research is recommended to incorporate additional determinants such as education quality, internet accessibility, and social capital to provide a more comprehensive understanding of digital workforce readiness in the context of rapid technological transformation.

Acknowledgements

The authors would like to express their gratitude to all parties who provided constructive feedback during the preparation of this manuscript, despite the study receiving no external funding or support.

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Received: 27 November 2025

Accepted: 29 April 2026

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