Original Research Article

A Spatial Analysis of AI Adoption Across U.S. States Using Economic and Demographic Indicators

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ABSTRACT

The rapid adoption of artificial intelligence (AI) across industries has prompted increasing interest in understanding its geographic distribution and underlying causes. This study investigates the factors and spatial characteristics of AI adoption across U.S. states using recent data from the U.S. Census Bureau's Business Trends and Outlook Survey (BTOS), combined with state-level economic and demographic indicators. Specifically, the analysis incorporates gross domestic product (GDP), population, and unemployment rate as explanatory variables. A comprehensive methodological framework is employed, including Global Moran's I for spatial autocorrelation analysis, ordinary least squares (OLS) regression, and spatial lag models based on both contiguity and distance-based weighting schemes. The results indicate that AI adoption exhibits no statistically significant spatial autocorrelation, suggesting a lack of geographic clustering across states. Furthermore, regression analysis indicates that even though GDP, population, and unemployment are related to AI usage, none of these variables are statistically significant predictors at conventional levels. Spatial lag models yield consistent findings, with insignificant spatial autoregressive coefficients, confirming the absence of meaningful spatial dependence. Model performance comparisons demonstrate that incorporating spatial effects does not improve explanatory power. These findings suggest that AI adoption in the United States is largely distributed and influenced more by localized, non-spatial factors than by regional spillover effects. The study emphasizes the need for incorporating more variables and finer spatial resolution in future research to better capture the complexity of technology adoption.

Keywords: Artificial Intelligence Adoption; Spatial Analysis; Moran's I; Spatial Lag Model; Ordinary Least Squares; Economic Indicators; U.S. States; Technology Diffusion

INTRODUCTION

Artificial intelligence (AI) has transformed industries in recent decades due to advancements in computational hardware and algorithmic design (1). AI has become a critical tool for improving efficiency and productivity in finance, healthcare, and logistics (2, 3). Furthermore, AI is also considered an important strategic resource in global competition, so governments and corporations heavily invest in its development and implementation. Since AI is growing rapidly, researchers have become more interested in studying the factors and patterns related to AI adoption.

AI adoption varies across different geographic areas due to economic and demographic reasons, such as GDP, population size, and unemployment rate (4). Large

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scale and consistent datasets of AI are limited because it is a recently widespread technology (5). This poses challenges to researchers who want to identify and quantify AI adoption factors.

AI adoption may also show spatial patterns. Nearby states often have similar economies, infrastructure, policy environments, and innovation ecosystems. This can lead to spatial dependence in AI usage (6). Neighboring states can affect each other through sharing labor markets, ideas, and having similar investments (7, 8). Normal statistical methods may miss these geographic connections. To address this issue, spatial analysis allows researchers to study geographic relationships and identify clusters.

Previous research has studied technological adoption and economic indicators separately (9, 10). However, only a limited number of studies have compared different spatial weighting approaches, such as adjacency-based (contiguity), distance-based weights, and spatial autocorrelation measures (e.g. Moran's I), in the context of AI adoption patterns.

To address this research gap, this study uses data from the U.S. Census Bureau's Business Trends and Outlook Survey (BTOS) with state-level economic and demographic data, including GDP, population, and unemployment rates. By incorporating multiple spatial weighting schemes and evaluating spatial autocorrelation using Moran's I, this study aims to test how different spatial weighting structures affect modeling results and to gain a better understanding of the geographical patterns associated with AI adoption.

The results of this study can help people better understand the economic factors and spatial characteristics of AI adoption. By analyzing how factors associated with AI adoption can be related to geographical location, this study contributes to a better understanding of technology in the economy. The results may help inform policymakers, business leaders and researchers in areas such as investment, workforce planning, and regional development initiatives. Overall, this study aims to bridge the gap between economic analysis and spatial modeling in the context of emerging technologies such as AI.

METHODS AND MATERIALS

This study uses a combination of spatial statistical analysis and regression modeling to investigate the determinants and spatial characteristics of AI adoption across U.S. states. The methodological framework comprises four main parts: 1) global spatial autocorrelation analysis using Moran's I, 2) ordinary least squares (OLS) regression, 3) a spatial lag model using contiguity-based weights, and 4) a spatial lag model using distance-based weights. These approaches allow for both spatial and non-spatial relationships to be observed in a systematic way.

Data Description

This study uses state-level data to analyze the factors and spatial patterns of artificial intelligence (AI) adoption across the United States. The dependent variable, AI usage (AI_use), is obtained from the U.S. Census Bureau's Business Trends and Outlook Survey (BTOS) AI supplement, which reports pooled estimates from data collected between December 4, 2023, and February 25, 2024. The dataset was downloaded on March 14, 2026. The data can be accessed through the official Census Bureau portal: https://www.census.gov/hfp/btos/data. The AI usage variable represents the percentage of businesses in each state that report using AI technologies in their operations. The final analytical dataset includes 51 spatial units, consisting of the 50 U.S. states and the District of Columbia. BTOS estimates for five states (Alaska, North Dakota, South Dakota, West Virginia, and Wyoming) were suppressed. To retain these jurisdictions in the spatial analysis, the suppressed values were imputed using the overall mean AI adoption rate of approximately 16%.

Additional economic and demographic variables are incorporated along with the AI usage data, including gross domestic product (GDP), total population, and unemployment rate. These variables are widely accepted in literature as key macro-level indicators influencing technological adoption. GDP data are obtained from the U.S. Bureau of Economic Analysis (BEA), SAGDP1: State annual gross domestic product (GDP) summary, using 2024 values measured in millions of chained 2017 dollars, retrieved on March 20, 2026. Population data are obtained from the U.S. Census Bureau, Population Division, Annual Estimates of the Resident Population for the United States, Regions, States, District of Columbia, and Puerto Rico: April 1, 2020 to July 1, 2025 (NST -EST2025-POP), using 2025 estimates measured in number of persons, retrieved on March 20, 2026. Unemployment data are obtained from the U.S. Bureau of Labor Statistics (BLS), State Unemployment rates, December 2025, seasonally adjusted, using December 2025 data measured as a percentage, retrieved on March 20, 2026. GDP and population data are log-transformed (log_GDP and log_Pop) to account for scale differences and to improve model interpretability. The unemployment rate reflects labor market conditions and potential stimuli for automation.

All variables used in this study are obtained from the most recent available data, from 2024 and 2025, minimizing temporal mismatch. However, some differences in reference periods may remain. The use of multiple data sources allows for a comprehensive analysis of AI adoption from both economic and demographic perspectives.

Ultimately, the dataset uses multiple types of predictors: economic (GDP), demographic (population), and labor market indicators (unemployment rate) to provide a multifaceted view for analyzing AI adoption across states.

Global Moran's I Index

The study applies the Global Moran's I Index to determine whether AI adoption shows spatial dependence across states. Moran's I is a statistic widely used for measuring spatial autocorrelation, identifying if similar values cluster geographically.

The Global Moran's I is defined as:

$$I = \frac{N}{\Sigma_i \Sigma_j w_{ij}} \cdot \frac{\Sigma_i \Sigma_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\Sigma_i (x_i - \bar{x})^2}$$

where N is the number of spatial units (states), x_i and x_j represent AI usage values in states i and j, $\underline{x}$ is the mean AI usage, and w_{ij} is the spatial weight between states i and j.

The expected value of Moran's I under spatial randomness is:

$$E[I] = -\frac{1}{N-1}$$

Spatial weights were constructed using both Queen contiguity and k-nearest-neighbor (KNN) approaches. The analysis included 51 spatial units, consisting of the 50 U.S. states and the District of Columbia; Puerto Rico was excluded. For the Queen contiguity matrix, states sharing a boundary or vertex were treated as neighbors, and the resulting weights were row-standardized. For the distance-based specification, a KNN matrix with k = 4 was constructed using the centroids of the state geometries. The geographic data were projected to EPSG:2163 before centroid coordinates were used to construct the KNN weights, and the resulting KNN weights were row-standardized. The KNN matrix used Euclidean distance, ties between equally distant neighbors were arbitrarily resolved by the KNN algorithm, and the resulting weights were row-standardized. The KNN matrix was not explicitly symmetrized. A positive Moran's I value indicates positive spatial autocorrelation, in which similar values tend to cluster geographically, whereas a negative value indicates negative spatial autocorrelation, in which dissimilar values tend to be spatially associated. The significance of the results is determined based on z-scores and permutation-based p-values.

Ordinary Multiple Linear Regression Model

An ordinary multiple linear regression model was estimated to analyze the relationship between AI adoption and economic/demographic factors. The model specification is given by:

$$AI_i = \beta_0 + \beta_1 log(GDP_i) + \beta_2 log(Pop_i) + \beta_3 Unemp_i + \epsilon_i$$

where AI_i is the AI usage level in state i, $log(GDP_i)$ is the natural logarithm of GDP, $log(Pop_i)$ is the natural logarithm of population, $Unemp_i$ is the unemployment rate, and ϵ_i is the error term.

Logarithmic transformations are applied to GDP and population to reduce the influence of extreme differences in scale and improve model interpretability. The OLS model assumes that observations are independent and homoscedastic and that there is no geographic dependence. Model performance is evaluated with R^2, F-statistic, and error metrics such as root mean square error (RMSE) and mean absolute error (MAE).

Table 1. *Summary Statistics of Variables Used in the Study.*

Variable	Description	Unit	Mean	Median	Std. Dev.
AI_use	Percentage of firms using AI (BTOS)	%	16.6	16	3.5
GDP	Gross Domestic Product by state	Million USD	610,000	353,000	720,000
Population	Total state population	Persons	6,500,000	4,600,000	7,300,000
Unemployment Rate	State unemployment rate (Dec 2025)	%	4	4	0.9

Linear Model with Contiguity Spatial Lag

To account for possible spatial interactions between neighboring states, a spatial lag model (SLM) was estimated based on contiguity weights. This model integrates the influence of AI adoption levels in neighboring states directly into the regression framework.

The spatial lag model is defined as:

$$AI_i = \rho \sum w_{ij} AI_j + \beta_0 + \beta_1 log(GDP_i) + \beta_2 log(Pop_i) + \beta_3 Unemp_i + \epsilon_i$$

where ρ is the spatial autoregressive coefficient, representing the strength of spatial dependence, and $\Sigma_j w_{ij} AI_j$ is the spatial lag of the dependent variable.

The contiguity weight matrix is constructed using the Queen criterion, where neighboring states share a common boundary or vertex. The matrix is row-standardized so that the weights sum up to one for each state. If it is statistically significant, it shows that AI adoption in a certain state is influenced by neighboring states. Otherwise, spatial dependence is considered negligible.

Linear Model with Distance Spatial Lag

Spatial dependence is also examined using a distance-based lag model. This strategy captures interactions based on geographic closeness instead of shared boundaries.

The model specification is identical to the contiguity-based spatial lag model:

$$AI_i = \rho \sum w_{ij} AI_j + \beta_0 + \beta_1 log(GDP_i) + \beta_2 log(Pop_i) + \beta_3 Unemp_i + \epsilon_i$$

However, the spatial weights are defined using a k-nearest neighbors (KNN) approach, where each state is connected to its four closest neighbors (k=4) based on geographic distance. This specification allows the model to capture interactions between states that do not share immediate borders. Similar to the contiguity model, the spatial lag coefficient is used to determine the presence and strength of spatial dependence.

Ultimately, the combination of Moran's I analysis, OLS regression, and spatial lag models with different weighting schemes allows for a comprehensive framework for evaluating both spatial and non-spatial determinants of AI adoption. This multi-model approach allows for robust comparison and validation of results in different spatial assumptions.

Principal Component Analysis for Visualization

Principal component analysis (PCA) was used to visualize the relationship between the predictor variables and the fitted values from the regression models. The PCA included three predictor variables: log-transformed gross domestic product (log_GDP), log-transformed population (log_Pop), and unemployment rate. Prior to PCA, the predictor variables were standardized using the StandardScaler procedure. PCA was performed with one component (n_components = 1), producing the first principal component (PC1) as a one-dimensional summary of the standardized predictor variables. Figures 3–5 display the observed AI adoption values and fitted values from the ordinary least squares (OLS), contiguity-based spatial lag, and distance-based spatial lag models, respectively, against PC1. PCA was used solely for visualization and was not used as a predictor in the estimation of the regression models.

Principal Component 1 (PC1) explained 72.6% of the total variance among the standardized predictor variables (eigenvalue = 2.22). PC1 had positive coefficients of 0.661 for log-transformed GDP, 0.644 for log-transformed population, and 0.385 for unemployment rate. Therefore, higher PC1 scores generally represented states with larger economies, larger populations, and higher unemployment rates. PC1 was used only for visualization in Figures 3–5 and was not included as a predictor in the regression models.

RESULTS

Global Moran's I Index Analysis

The global spatial autocorrelation of AI adoption across U.S. states was assessed with Moran's I under two spatial weighting schemes: contiguity-based (queen) and distance-based (k-nearest neighbors with k = 4). As shown in Table 2, the Moran's I values are 0.004 for contiguity weights and 0.020 for distance weights. Both

Table 2. *Global Moran's I Index.*

weights_type	moran_I	expected_I	z_score	p_value_norm	p_value_perm
contiguity_queen	0.004	-0.020	0.249	0.803	0.413
distance_knn_k4	0.020	-0.020	0.456	0.649	0.309

values are close to zero. The expected Moran's I value under spatial randomness was −0.020 for both weighting schemes. The z-scores (0.249 and 0.456, respectively) and p-values greater than 0.05 for both the normality-based and permutation tests indicate that neither Moran's I statistic is statistically significant.

The Moran scatter plots (Figures 1 and 2) visually support this conclusion, showing that there is no clear clustering pattern in either high-high or low-low regions, with observations appearing relatively dispersed. Overall, neither the contiguity-based nor distance-based statistic was statistically significant.

Ordinary Multiple Linear Regression Model Results

An ordinary least squares (OLS) regression model was conducted to determine whether economic and demographic variables, including GDP, population size, and unemployment rate are associated with AI usage. The results, shown in Table 3, indicate that none of these variables are statistically significant at the conventional 0.05 level. Log-transformed GDP has a positive coefficient (2.883), suggesting a possible positive association with AI adoption, but its p-value (0.143) indicates that this relationship is not statistically significant. Similarly, population (coefficient = -1.755, p = 0.360) shows a negative but insignificant relationship, while unemployment rate (coefficient = 0.277, p = 0.622) shows a weak and statistically insignificant positive effect.

Although there is no individual significance, the overall model is statistically meaningful. It has an F-statistic of 4.281 and a corresponding p-value of 0.009,

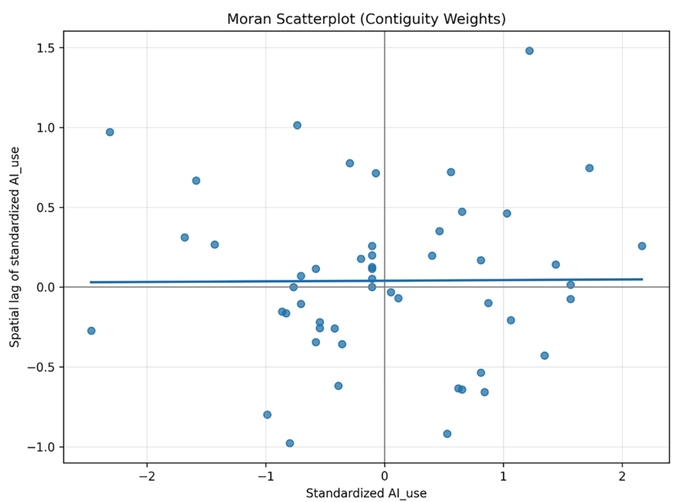

Figure 1. *Moran Scatter Plot based on Contiguity Weights. The plot displays standardized AI adoption values against their spatially lagged values using a Queen contiguity weighting matrix. States sharing a boundary or vertex are treated as neighbors, and the weights are row-standardized. The horizontal axis represents the standardized AI adoption value, while the vertical axis represents the corresponding spatial lag.*

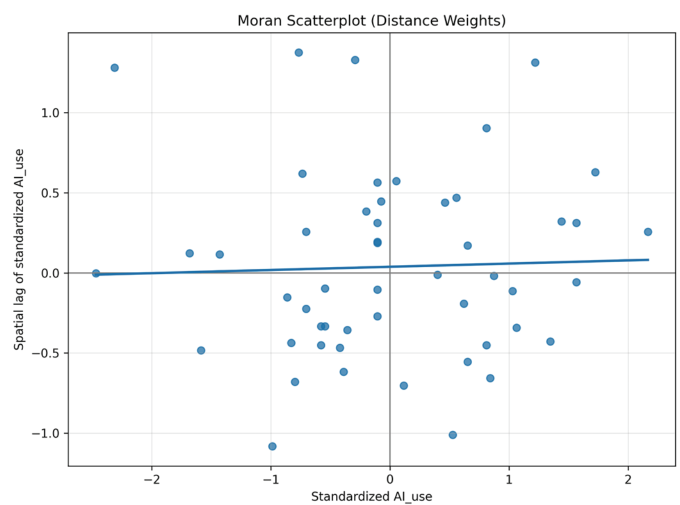

Figure 2. *Moran Scatter Plot Based on Distance Weights. The plot displays standardized AI adoption values against their spatially lagged values using a k-nearest-neighbor (KNN) weighting matrix with k = 4. The KNN weights are based on centroid coordinates using Euclidean distance and are row-standardized. The horizontal axis represents the standardized AI adoption value, while the vertical axis represents the corresponding spatial lag.*

Table 3. *Multiple Linear Regression Model Results for AI Use.*

variable	coefficient	std_error	t_value	p_value	conf_low	conf_high
const	5.984	7.903	0.757	0.453	-9.916	21.883
log_GDP	2.883	1.937	1.489	0.143	-1.013	6.779
log_Pop	-1.755	1.897	-0.925	0.360	-5.572	2.062
Unemployment rate	0.277	0.558	0.497	0.622	-0.846	1.400

meaning the variables jointly explain some variation in AI usage. The model achieves an R^2 of 0.215, suggesting a modest explanatory power. Figure 3 shows the general trend portrayed by the regression model.

Modeling Results with Contiguity Spatial Lag

To account for possible spatial dependence, a spatial lag model incorporating contiguity-based weights was estimated. The results in Table 4 show that the coefficients of the variables remain mostly consistent with the results from the OLS model. Log GDP continues to exhibit a positive relationship with AI usage (coefficient = 2.857), while population retains a negative association (coefficient = -1.724), and unemployment rate shows a small positive effect (coefficient = 0.293). Nonetheless, similar to the OLS model, none of these results are statistically significant.

The spatial lag parameter (ρ) is estimated at -0.013 with a p-value of 0.902, indicating that the spatial autoregressive effect is statistically insignificant. Figure 4 also shows that the fitted trend remains nearly identical to the OLS results, reinforcing the conclusion that spatial interaction among neighboring states does not play a significant role in shaping AI adoption patterns.

Modeling Results with Distance Spatial Lag

A second spatial lag model was estimated using distance-based weights (k-nearest neighbors). As shown in Table 5, the estimated coefficients are very consistent

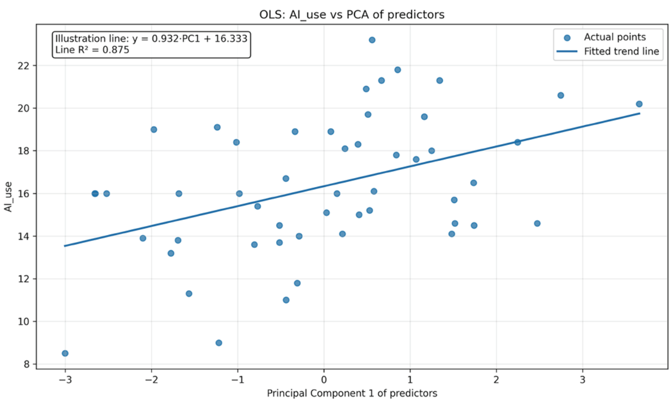

Figure 3. *Trend Line of AI Use Based on the Ordinary Linear Regression Model. Principal Component 1 (PC1) of predictors is plotted against the fitted AI adoption estimated from the OLS model using log-transformed GDP, log-transformed population, and unemployment rate as predictors. The fitted values represent the model's predicted AI adoption values based on the estimated OLS coefficients. The displayed trend line is an illustrative linear fit between PC1 and the OLS-fitted values and is included only for visualization. It does not represent an additional regression model used in the analysis.*

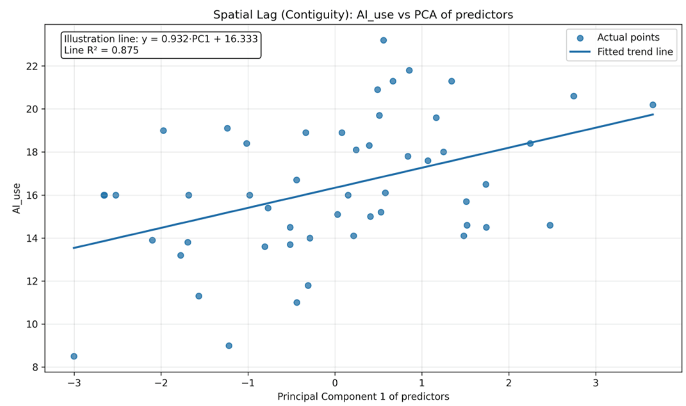

Figure 4. *Trend Line of AI Use Based on the Linear Regression Model with Contiguity Spatial Lag. Principal Component 1 of predictors is plotted against fitted AI adoption (%) estimated from the spatial lag model using Queen contiguity weights. The spatial weights are row-standardized, and the model includes log-transformed GDP, log-transformed population, unemployment rate, and a spatial lag parameter (ρ). The fitted values represent the model's predicted AI adoption values based on the estimated coefficients and spatial lag structure. The displayed trend line is an illustrative linear fit between PC1 and the fitted values and is included only for visualization.*

Table 4. *Modeling Results with Contiguity Spatial Lag for AI Use.*

variable	coefficient	std_error	z_value	p_value
CONSTANT	5.974	7.600	0.786	0.432
log_GDP	2.857	1.872	1.526	0.127
log_Pop	-1.724	1.846	-0.934	0.350
Unemployment rate	0.293	0.543	0.539	0.590
rho	-0.013	0.109	-0.123	0.902

Table 5. *Modeling Results with Distance Spatial Lag for AI Use.*

variable	coefficient	std_error	z_value	p_value
CONSTANT	5.502	8.091	0.680	0.497
log_GDP	2.873	1.860	1.544	0.123
log_Pop	-1.740	1.823	-0.955	0.340
Unemployment rate	0.268	0.538	0.499	0.618
rho	0.025	0.195	0.127	0.899

with the OLS and contiguity-based spatial lag models. Log GDP (coefficient = 2.873) maintains a positive but insignificant relationship with AI usage, while population (coefficient = -1.740) and unemployment rate (coefficient 0.268) remain statistically insignificant.

The spatial lag parameter (ρ) is estimated at 0.025 with a p-value of 0.899, indicating no statistically significant spatial dependence under the distance-based weighting scheme. The trend line in Figure 5 is similar to those of the previous models.

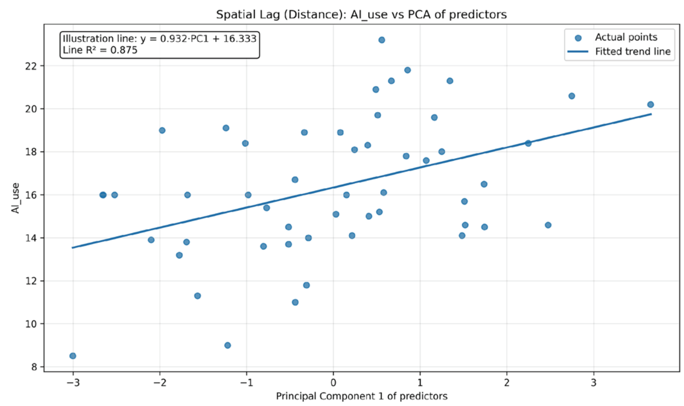

Figure 5. *Trend Line of AI Use Based on the Linear Regression Model with Distance Spatial Lag. Principal Component 1 of predictors is plotted against fitted AI adoption (%) estimated from the spatial lag model using a k-nearest-neighbor (KNN) weighting matrix with k = 4. The KNN weights are based on centroid coordinates using Euclidean distance and are row-standardized. The model includes log-transformed GDP, log-transformed population, unemployment rate, and a spatial lag parameter (ρ). The fitted values represent the model's predicted AI adoption values based on the estimated coefficients and spatial lag structure. The displayed trend line is an illustrative linear fit between PC1 and the fitted values and is included only for visualization.*

Model Performance Comparative Results

The performance of the OLS and spatial lag models was compared using multiple evaluation metrics, including R^2 (or pseudo-R^2), RMSE, MAE, Akaike information criterion (AIC), and log-likelihood. As shown in Table 6, all models exhibit almost identical explanatory power, with R^2 or pseudo-R^2 values of approximately 0.215. The error metrics (RMSE ≈ 2.811-2.812 and MAE ≈ 2.297-2.309) are also very similar across models, indicating comparable accuracy.

In terms of model fit, the spatial lag models show only small differences in AIC and log-likelihood values compared to the OLS model. For instance, the AIC values for the spatial lag models (260.154 and 260.157)

Table 6. *Model Performance Comparative Results.*

model	R2/pseudo_R2	rmse	mae	aic	log_likelihood	schwarz bic	f_statistic	f_pvalue
OLS	0.215	2.812	2.305	258.172	–	–	4.281	0.009
SpatialLag_Contiguity	0.215	2.811	2.309	260.157	-125.079	269.816	–	–
SpatialLag_Distance	0.215	2.811	2.297	260.154	-125.077	269.813	–	–

Note: R^2 = coefficient of determination; pseudo-R^2 = pseudo-coefficient of determination; RMSE = root mean square error; MAE = mean absolute error; AIC = Akaike information criterion; BIC = Bayesian information criterion; KNN = k-nearest neighbors. The spatial lag models use contiguity-based and distance-based spatial weighting schemes, respectively. The distance-based spatial lag model uses k = 4 nearest neighbors. F-statistic and F p-value are reported for the OLS model only. Dashes indicate statistics that are not reported or are not directly applicable to the corresponding model.

are slightly higher than the value of the OLS model (258.172), indicating no significant improvement in model performance. Furthermore, the Schwarz Bayesian Information Criterion (BIC) values are very similar in both spatial models.

DISCUSSION

Implications

The findings of this study offer multiple insights for understanding how AI adoption varies across U.S. states. First, the absence of statistically significant spatial autocorrelation, as shown in the Moran's I analysis and the insignificant spatial lag parameters in both contiguity and distance-based models, suggests that AI adoption does not exhibit a strong geographic pattern. The trend line in Figure 5 closely resembles trend lines from previous models. This suggests that incorporating distance-based spatial structure does not significantly change the model outcomes. The lack of statistically significant spatial lag parameters also suggests that incorporating spatial dependence does not substantially improve the models' ability to explain AI adoption. States with similar AI usage levels are not consistently grouped together, indicating that location alone may not be a factor of AI adoption. This is a notable result because it indicates that states are not constrained or influenced by regions that are close by when adopting AI technologies. These findings suggest that state-specific economic conditions, policies, and institutional environments may play a greater role in AI adoption than geographic spillover effects.

The comparative results demonstrate that incorporating spatial lag structures does not significantly improve model performance, whether based on contiguity or distance. This is consistent with the earlier results from the Moran's I analysis, strengthening the conclusion that spatial dependence is insignificant in explaining AI adoption across U.S. states.

Second, the regression results suggest that traditional macro-level indicators such as GDP, population, and unemployment rate do not have a statistically significant influence on AI adoption in this model. This indicates that AI usage rates may change due to other factors, including industry composition, digital infrastructure, workforce skills, education levels, or firm-level innovation capacity instead of just broad aggregate indicators. The modest explanatory power of the model ($R^2 \approx 0.215$) further strengthens the idea that AI adoption is complex and cannot be fully captured by a limited set of macroeconomic variables.

These findings indicate that AI diffusion in the United States may be more decentralized and heterogeneous than expected. Policymakers should consider state-specific strategies instead of depending on regional or geographically coordinated approaches. Moreover, the lack of spatial dependence implies that successful AI adoption strategies in one state may not automatically spill over to neighboring states without policy intervention or institutional support.

Limitations

Although it contributes to the field, this study has several limitations that should be acknowledged. First, even though key economic and demographic factors, such as GDP, population, and unemployment rate were included, the model does not capture many other factors that might be important in studying AI adoption rates. Variables, including education level, research and development (R&D) investment, broadband access, industrial structure, and firm-level technological readiness may play big roles but were not included in the study due to limited amounts of data available. The omission of these variables may partially explain the relatively low explanatory power of the models and the lack of statistical significance among the included predictors.

Second, the analysis is conducted at the state level, which may be too broad to capture important regional differences in AI adoption. AI usage is often highly localized with significant differences across metropolitan areas, counties, or individual firms. Using state-level data may overlook important intrastate heterogeneity and reduce the ability to detect spatial patterns. Future research using finer spatial findings, such as county-level or metropolitan statistical area (MSA)-level data, could provide more detailed results and possibly uncover spatial dependencies that are not found in state level data.

Third, the measurement of AI usage itself is subject to limitations. Although it is valuable, the BTOS dataset consists of survey-based estimates that may include biases or inconsistencies across states. Moreover, AI being used as a widespread technology is relatively new. This signifies that longitudinal data are limited, making it more difficult to analyze temporal dynamics or causal relationships over time.

Finally, the spatial modeling approaches used in this study focus on relatively basic spatial lag structures. Even though it is useful for initial analysis, more advanced spatial econometric models, such as spatial error models, spatial Durbin models, or geographically weighted regression (GWR), may provide more insights into localized effects and spatial heterogeneity.

Recommendations

Based on the modeling results, several policy and research recommendations can be proposed. First, states should focus on creating their own tailored AI strategies due to the result that there was no significant spatial dependence. States should not rely on neighboring states' spillover effects. Investments in AI infrastructure should be based on the specific needs of each state. For example, states with higher economic capacity may focus on scaling advanced AI applications, while others may prioritize foundational investments in digital infrastructure and education.

Second, although the coefficients for GDP, population, and unemployment rate are not statistically significant, GDP still shows a positive trend. Economic resources may contribute to AI adoption. Therefore, policies that support economic growth, such as tax incentives for AI adoption, public-private partnerships, and funding for research institutions, may indirectly promote AI diffusion.Although the unemployment coefficient is positive, the relationship is not statistically significant. Therefore, the results do not provide sufficient evidence to conclude that unemployment is associated with AI adoption. Nevertheless, workforce training and reskilling remain important areas for future research and policy consideration as AI adoption continues to expand.

Third, the results emphasize that incorporating additional explanatory variables in future modeling efforts is essential. Policymakers and researchers should prioritize collecting more detailed data on digital infrastructure, education, industry sectors, and firm-level innovation. Improving data availability will allow for more accurate modeling and better-informed decision-making.

Fourth, future research should use smaller geographic units, such as county-level or city-level analyses. Future research should also try more advanced spatial econometric models. Trying these alternatives might be able to uncover localized clustering effects and provide more practical results. Furthermore, longitudinal studies could be used to help identify causal relationships and track AI adoption over time.

In conclusion, while this study finds limited evidence of geographic clustering and weak statistical relationships among the selected variables, it highlights the importance of localized policy design, improved data collection, and more advanced analytical approaches in understanding and promoting AI adoption.

CONCLUSION

The findings of this study indicate that there is no statistically significant spatial autocorrelation for AI adoption. The analysis reveals that while factors, including GDP, population, and unemployment rate are related to AI usage, these variables are not statistically significant indicators at conventional levels. These findings suggest the need for incorporating additional variables and finer spatial-resolution data in future research. While this study focused on state level data, future research could use more localized data to uncover more detailed results that were overlooked when using state data. Even though this study did not find much evidence of spatial autocorrelation in AI usage and statistically insignificant relationships among the selected variables, it calls for better data collection, localized policy design, and more complex analytical methods in order to fully understand AI adoption.

CONFLICT OF INTEREST

The author declares that there are no conflicts of interest related to this work.

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