ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Technology Empowerment and Value Remodeling: The Influence Mechanism of Digital Economy on the Evolution of Commercial Space around Zhengzhou Rail Transit Stations

Guimin Ma[1] *and Jialin Hou*[1,*]

[1] School of Architecture and Urban Planning, Henan University of Urban Construction, Pingdingshan, Henan, 467036, China

SUMMARY: *The digital economy has become a major force shaping the expansion of commercial layouts. This study focuses on the business districts around stations along Zhengzhou Metro Line 1. Using panel data from 2014 to 2024 collected from SDE, KD, CV, and buffer overlay indicators, the paper examines the spatial evolution of the area. An individual fixed-effects panel model is constructed by integrating relevant datasets and characteristic variables associated with the digital economy. Through regression estimation, the study explores how digital-economy-related factors affect the development of commercial space. The results indicate that changes in firm space are positively and significantly associated with the platform economy, the sharing economy, and mobile payment systems (P<0.001), while the four crowds model, artificial intelligence applications, and blockchain applications are also significant at the 0.05 level..*

KEYWORDS: *digital economy; individual fixed effects model; regression analysis; commercial space evolution; Zhengzhou rail transit*

1 Introduction

Since the beginning of the twenty-first century, as urbanization has accelerated, a phenomenon known as "urban disease" has become more severe. The main issues that many people face on a daily basis are the growing pressure of urban traffic, urban traffic congestion, and travel difficulties [1, 2]. As a unique form of transportation for city dwellers, rail transit's contribution to reducing traffic congestion and maximizing the dispersion of urban industries cannot be overlooked. It has also progressively been included into urban planning initiatives carried out by all levels of government [3, 4]. By the end of 2023, rail transit was operational in 55 cities in Mainland China, with a total length of more than 14,000 km and a projected total mileage of more than 20,000 km by 2030. By the end of 2025, Zhengzhou Rail Transit featured various lines, an interstate railway, a subway, and a municipal light rail.

With the completion of Zhengzhou rail transit, by virtue of its “large capacity, high speed, punctuality” advantage, has profoundly changed the travel mode of urban residents and spatial and temporal perception, and the commercial sector as a dependence on the flow of people and traffic development of the economy, its layout, structure and vitality will inevitably by the construction of rail transit significant impact [5, 6]. From the practical point of view, urban rail transit construction and commercial development presents the characteristics of “two-way empowerment”, rail transit for business to bring stable passenger flow and convenient

*ArcM009@163.com
https://doi.org/10.65102/is2026414 Published: 30 April, 2026

accessibility to promote the upgrading of commercial business; business for rail transit stations to provide “passenger anchoring” effect The commercial sector provides a “passenger anchoring” effect for rail transit stations, which enhances the operational efficiency and social value of rail transit [7-12]. The evolution of commercial space around rail transit stations can reflect the urban metro economy, commercial economic vitality, and urban spatial pattern [13, 14].

The digital economy has progressively grown to be a significant driver propelling the growth of the global economy and industries against the backdrop of the global economy's expansion and changes in industrial structures. One way to support industrial economic growth is by using digital technology to optimize industries and improve consumer services [15, 16]. Additionally, through smart cities, digital governance, smart manufacturing, mobile payments, and online-offline integration, the digital economy improves urban residents' quality of life and fosters the superior growth of the urban economy [17-19]. The digital economy has impacted the growth of urban railway transportation as the primary component of urban development [20]. Examining how the digital economy affects the growth of companies close to train stations in cities can be beneficial for improving both economic growth and quality of life.

In this paper, from the analysis of characteristics and model regression, a case study is conducted on Zhengzhou Metro Line 1 to examine how the development of the digital economy influences the evolution of commercial space around rail transit stations, thereby providing data support for understanding changes in rail commercial space and forecasting future development trends. For the four types of characteristics of commercial outlet agglomeration scale, agglomeration density, distribution range, and spatial distribution direction, four types of analytical methods, including standard deviation ellipse (SDE), kernel density estimation (KD), coefficient of variation (CV), and buffer superposition, are employed to reconstruct the process of commercial space evolution around the stations of Zhengzhou Metro Line 1. Seven categories of characteristics are selected as the influencing elements on the business space sample data, in addition to the formal characteristics of the digital economy. The panel data model is selected using the F-test, Hausman test, heteroskedasticity and autocorrelation tests, etc., and eventually takes the shape of an individual fixed-effects model. The digital economy and business space characteristics connected to the Zhengzhou Metro Line 1 stations will be compared in a regression model.

2 Characterization of the evolution of commercial space around Zhengzhou Metro Line 1

2.1 Overview of the development of Zhengzhou Metro Line 1

The Zhengzhou Metro Line 1's main alignment runs 41.5 km from West to East, from University H to University N New District. It began operations on January 1, 2014, and consists of 32 underground stations, ZJ being Metro Line 1's interchange station. Metro Line 1 coincides with the main axis of Zhengzhou's east-west development, passing through the four core areas of Zy District, Ey District, Js District and Gc District. Zhengzhou Metro Line 1 passes through Er Square business center and Zd New District CBD business center, strengthening the integrated development link between east and west urban areas.

2.2 Evolution of the spatial structure of commercial business and characterization methods

Spatial distribution is to characterize spatial variables and spatial objects from an overall, global perspective. This thesis takes GIS as a platform, according to the characteristics of commercial outlet data of Zhengzhou Metro Line 1, the distribution of commercial outlets is abstracted as a point pattern, and the spatial distribution of regional point locations is interpreted through the quantitative analysis of the points.In the thesis, standard deviation ellipse, kernel density analysis, coefficient of variation, buffer analysis, and superposition analysis are used to portray the distribution characteristics and changes of various types of business data points of Zhengzhou Metro Line 1.

2.2.1 Standard Deviation Ellipse Analysis (SDE)

The distributional properties of discrete point data sets are examined using the standard deviation ellipse (SDE) approach. The general distributional characteristics of commercial outlets from several dimensions are captured in this thesis using the standard deviation ellipse. In these situations, variations in the size of the elliptical area indicate the degree of dispersion of the outlets inside the corporate firm, while the long and short axes of the ellipse indicate the direction of the largest and smallest dispersion, respectively. The angle that separates the ellipse's long axis from its short axis in a clockwise direction is known as the deflection angle. The ellipse's east-west direction is 90.0°, and its north-south direction is 0.0° and 180.0°. The coordinates of the point data set are set as $(x_2, y_2), \cdots, (x_n, y_n)$, then the standard variance ellipse points to $\tan\theta$ (see Eq. 1), and the maximum standard deviation distance σ_x is the ellipse long-axis length, and the minimum distance σ_y is the ellipse's short-axis length (see Eq. 2 and Eq. 3).

$$\tan\theta = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2 - \sum_{i=1}^{n}(y_i-\bar{y})^2 + \sqrt{\left[\sum_{i=1}^{n}(x_i-\bar{x})^2 - \sum_{i=1}^{n}(y_i-\bar{y})^2\right]^2 + 4\left[\sum_{i=1}^{n}(x_i-\bar{x})^2 - \sum_{i=1}^{n}(y_i-\bar{y})^2\right]^2}}{2\sum_{i=1}^{n}\sum_{i=1}^{n}(x_i-\bar{x})\sum_{i=1}^{n}(y_i-\bar{y})} \tag{1}$$

$$\sigma_x = \sqrt{\sum_{i=1}^{n}\left[(x_i-\bar{x})\cos\theta - (y_i-\bar{y})\sin\theta\right]^2 / n} \tag{2}$$

$$\sigma_y = \sqrt{\sum_{i=1}^{n}\left[(x_i-\bar{x})\sin\theta - (y_i-\bar{y})\cos\theta\right]^2 / n} \tag{3}$$

where: $\bar{x}, \bar{y}$ is the average of x coordinate value and y coordinate value of all points respectively; θ is the rotation direction angle.

2.2.2 Kernel density estimation (KD)

Kernel density analysis is a widely used nonparametric estimation method in spatial analysis, calculating the value of the quantity per unit area in order to fit each point to a smooth conical surface. Kernel density estimation assumes that the point data can be distributed at any location in space, but its distribution probability is different at different spatial locations; a large distribution probability of the point data indicates that it is agglomerated; on the contrary, a small distribution probability of the point data indicates that it is dispersed. In the process of calculation, the point data falling within the search area are given different weight values, the closer to the center of the grid point data the greater the weight value. Its geometric significance is that the density is maximum at the center of each grid, decreasing to the periphery, when the density value at a certain threshold range from the center of the grid drops to 0.0, the kernel density value at the center of the grid x is the sum of the density values within the region. This thesis takes various types of outlets as the center of the circle, groups the outlets according to the natural fracture method, and estimates the hotspots of outlet concentration by calculating the density of the outlets in the unit area, in which the closer the center of the circle is, the higher the density is, and the denser the distribution of the outlets is, the bigger the scale is; the further the center of the circle is, the more sparse the distribution of the outlets is, and there is no distribution of the outlets in the limiting distance. In two-dimensional space, the kernel density function can generally be expressed as (see equation 4):

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{\pi r^2} \varphi\left(d_{ls}/r\right) \tag{4}$$

where $\lambda(s)$ denotes the kernel density value estimated at location s, r refers to the bandwidth, namely the search radius used in the kernel density function, n indicates the number of samples, and φ represents the distance-based weight associated with d_{ls} between locations l and s.

2.2.3 Coefficient of variation (CV)

The creation of polygons from the perpendicular bisectors of straight line segments joining two neighboring points is known as the Voronoi Diagram, also known as the Dirichlet Diagram or the Tyson Polygon. The closest neighbor principle, which divides the locations of the N distinct points in the plane into their corresponding nearest neighbor areas, is used to do this. As a function of the data's variability over time and space, the Voronoi Diagram's coefficient of variation offers an evaluation of the discretization characteristics of the point data's spatial distribution. The formula for its calculation is (see equations 5, 6, and 7):

$$CV = \left\{ \sigma / \mu \right\} \tag{5}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} \left(A_i - \mu\right)^2}{N-1}} \tag{6}$$

$$\mu = \frac{\sum A_i}{N} \left(\text{where } A_i \text{ denotes the area of the polygon}\right) \tag{7}$$

When the spatial distribution of a point set is regular, the CV value for that point is low. When the distribution is clustered, the area of the Voronoi polygon is small within clusters and large between clusters, the CV value is high.

2.2.4 Buffer Stacking Analysis

One kind of spatial analysis used to determine the impact of an object's immediate surroundings is buffer zone analysis. In this sense, the buffer zone may be thought of as a strip of a certain width that surrounds a geographic item in order to ascertain how much of an impact it has on nearby things. In terms of mathematics, the idea of a buffer zone is to locate a given spatial object's neighborhood. In this case, the neighborhood's radius R will determine its size. Thus the buffer of a spatial object O_i is defined as (see equation 8):

$$B_i = \left\{ x : d\left(x, O_i\right) \le R \right\} \tag{8}$$

That is, for an object set, each object O_i is associated with a buffer of radius R, and B_i denotes the collection of all points whose distance d from O_i does not exceed R. In most cases, d refers to the minimum Euclidean distance, although other distance measures may also be adopted. For the object set, the expression is given in equation (9).

$$O = \left\{ O_i : i = 1, 2, \cdots, n \right\} \tag{9}$$

The buffer of its radius R is the concatenation [50] of the individual object buffers, i.e., (see Eq. 10):

$$B = Y_{i=1}^{n} B_i \tag{10}$$

Commonly used buffers are buffer analysis for points, buffer analysis for lines and buffer analysis for surfaces, where point elements are simpler and line and surface elements are more complex.

In order to create a new level of multiple attribute combination based on the intersections between elements and polygon boundaries or attributes of polygons, as well as to conduct a thorough analysis and evaluation of their intrinsic connection and development laws, overlay analysis involves superimposing two or more themes of data with the same location, scale, and mathematical foundation but different modes of expression. According to the different objects of operation, it can be divided into the overlay of points and polygons, the overlay of lines and polygons, and the overlay analysis of polygons and polygons.

The buffer analysis done in this thesis is based on the line buffer analysis of Zhengzhou Metro Line 1, which establishes equal buffer polygons on both sides of the road according to a fixed distance in GIS, and then generates a new layer by overlaying the buffer surface data and the point data of commercial outlets, and analyzes the correlation between the two through the discrimination of their positional relationship.

2.3 Commercial agglomeration pattern and spatial evolution in the site vicinity

2.3.1 There is a significant gap in the scale of commercial outlet agglomeration at the site

With the opening of Zhengzhou Metro Line 1, the commercial outlets around the stations have increased to different degrees, but there is an obvious gap in the number of commercial outlets at the stations. The statistics results of the number of commercial outlets at the 24 Zhengzhou Metro Line 1 stations in 2014 and 2024 are displayed in Table 1.

The average number of commercial outlets at each station increases from 556.75 in 2014 to

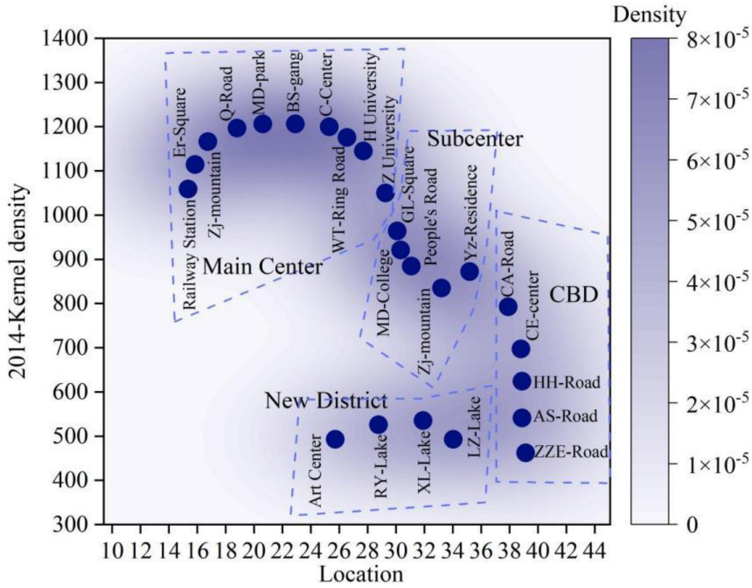
930.292 in 2024, Er Square Station increases from 3414 to 5274, the increase is in the first place of the station, Er Square Station is located in the center of the municipal business district, the commercial attraction is strong, the opening of the station further enhances its prosperity and the clustering effect of the commercial center.Yz Mountain Village, Q Road, LZ Lake and CA Road station also increased by more than 540, these stations have been built for a longer time and the surrounding environment is more developed, attracting more commercial outlets to gather. The smaller increases in outlets were in MD College (56), Train Station (63), GL Plaza (42) and C Center Station (80). Commercial concentration also showed some improvement, with a larger increase in the average geographic concentration index for each station, and the opening of the subway strengthened the relative concentration of commercial services around these stations.

Table 1: Number of commercial outlets at 24 stations in 2014 and 2024

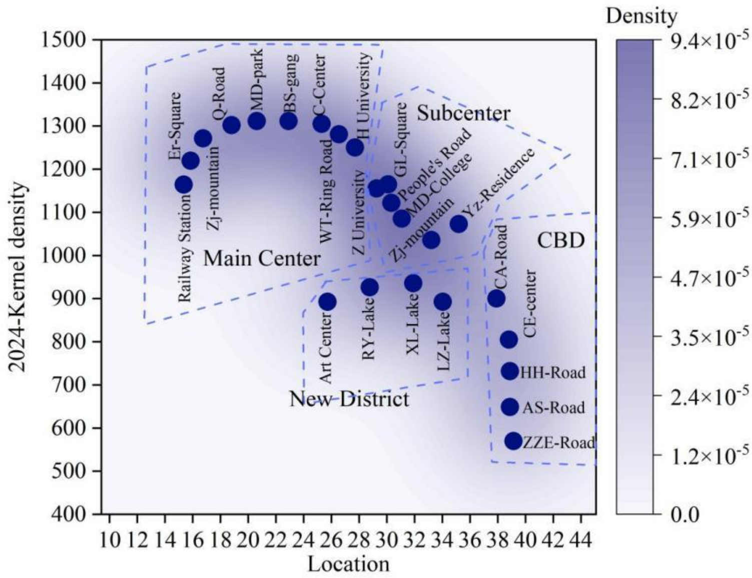
Site	2014	2024	Site	2014	2024
H University	76	285	Zj-mountain	682	806
Z University	55	271	Yz-Residence	1147	2217
C-Center	81	161	CA-Road	299	883
WT-Ring Road	137	260	CE-center	264	616
Q-Road	698	1463	HH-Road	325	571
MD-park	725	983	AS-Road	91	243
BS-gang	1353	1736	ZE-Road	207	457
GL-Square	493	535	ZZE-Road	95	231
MD-College	622	678	LZ-Lake	42	585
Railway Station	239	302	XL-Lake	71	543
Er-Square	3414	5274	RY-Lake	54	328
People's Road	2095	2480	Art Center	97	619

2.3.2 Significant differences in commercial agglomeration densities at sites in different zones

Based on the full sample of commercial outlets POI data of Zhengzhou Metro Line 1 rail transit stations, Figure 1 carries out the kernel density analysis of commercial outlets, using the natural breakpoint method to classify and superimpose with the range of site commercial outlets agglomeration.The kernel densities of commercial outlets of the stations in a total of 4 areas of the main center, subcenter, new area, and BCD, which are passed by the Zhengzhou Metro Line 1 rail track, are all improved compared with that of 2014 in 2024. While the kernel density value of the four commercial outlets in the new area improves by nearly 400, the kernel density value of the CBD and the new area is still lower than the kernel density value of the commercial outlets in the main center and the sub-center. Among these, the kernel density of the commercial outlets in CA Road, CE Center, HH Road, AS Road, and ZZE Road in the CBD improves by about 100–200.It shows that the commercial agglomeration density of different district sites is affected by the development time.



(a) Density of commercial outlets in 2014



(b) Density of commercial outlets in 2024

Figure 1: Density of commercial outlets in 2014 and 2024

2.3.3 There is a clear differentiation in the distribution of commercial outlets at different ranges of the site

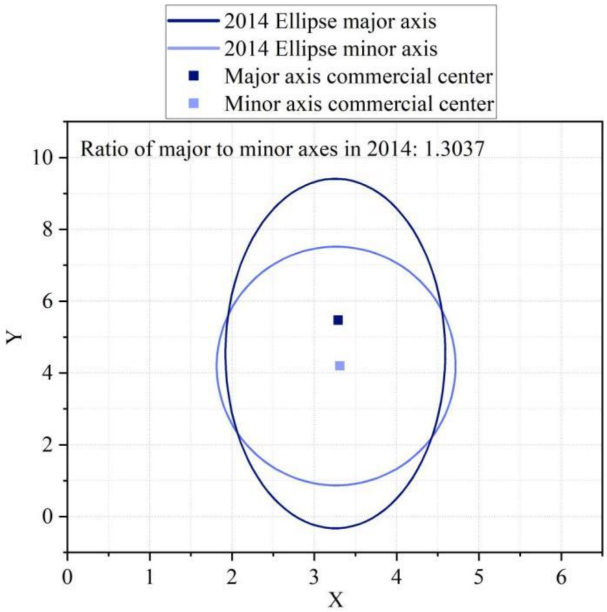
The number of commercial outlets and the distance from the station is not a monotonous function, but a low-high-low change. In order to guarantee the evacuation of the flow of people in and out of the station within a specific radius (the inner circle) less organized commercial, even if the dense flow of people in and out of the station might provide enormous business prospects, immediately adjacent to the inner circle of the middle circle is the most concentrated commercial outlets in the area, and thus outward with the increase in the distance from the station entrance, the density of commercial will be weakened, followed by the overall commercial space of the city and the overall business space in an orderly manner. Table 2 analyzes the number of commercial outlets within the 0~250m and 250~500m circles of 24 station entrances of Zhengzhou Metro Line 1. It can be seen that the number of outlets within 250m increased from 5,191 in 2014 to 6,163 in 2024, while the percentage decreased from 38.07% to 31.99%; the number of outlets within the 250~500m circle increased from 8,446 in 2014 to 13,105 in 2024, and the percentage increased from 61.93% to 68.01%, indicating that the station entrance of 250~500m is a commercial outlet cluster. 500m is the main area where commercial outlets are clustered.

Table 2: Scale of commercial facilities in different zones around the stations

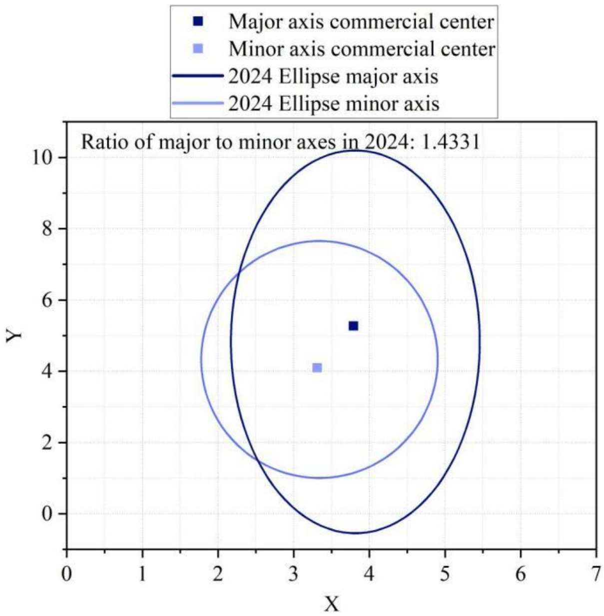
Site	0~250m		250~500m	
	2014	2024	2014	2024
H University	14	154	35	310
Z University	12	127	29	301
C-Center	35	148	67	288
WT-Ring Road	68	174	93	265
Q-Road	321	429	337	642
MD-park	476	582	556	753
BS-gang	365	494	401	543
GL-Square	148	285	203	487
MD-College	152	276	175	504
Railway Station	47	193	63	286
Er-Square	941	1554	1034	1376
People's Road	832	986	965	1175
Zj-mountain	372	479	453	758
Yz-Residence	658	784	695	1000
CA-Road	205	311	276	581
CE-center	87	207	127	543
HH-Road	16	165	40	397
AS-Road	53	178	69	401
ZE-Road	69	184	94	387
ZZE-Road	92	199	124	453
LZ-Lake	64	186	86	415
XL-Lake	28	165	54	426
RY-Lake	41	186	76	398
Art Center	95	201	111	416

2.3.4 Changes in the directional distribution of commercial space

Figure 2 uses standard deviation ellipse analysis to calculate the ellipse length-short axis ratio in 2014 and 2024 to study the relative position of the station area commercial center and the station, reflecting the attractiveness of the station as the center of the station area to the surrounding commercial outlets. The closer the ratio of the short and long axes is to 1, the more uniform and concentrated the distribution of commercial outlets.The ratio of the long and short axes of the ellipse in 2024 is 1.4331, which is larger than that of the ellipse in 2014, which is 1.3037.The commercial center of the station area is gradually shifted to the southeast, which is related to the development of the CBD and the new area of the station area, attracting more commercial outlets, and in the overall commercial outlets on the Metro Line 1 are in the state of increasing dispersion. Decentralized state.



(a) Ratio of major to minor axes in 2014



(b) Ratio of major to minor axes in 2024

Figure 2: Ratio of major axis to the minor axis of ellipse in 2014 and 2024

3 Empirical Analysis of Influential Factors of Commercial Space Distribution around Zhengzhou Rail Transit Stations

3.1 Selection of variables

Table 3 below lists the specific characteristics of the variables that were chosen for the modeling method. The Zhengzhou city's digital economy, which is made up of several elements, determines how commercial space is distributed around the Zhengzhou metro line. Platform economy, sharing economy, mobile payments, 3R technologies (virtual reality, augmented reality, and mixed reality), crowds four, artificial intelligence application, and blockchain application are some of the factors selected to explain the dependent variable. A1–A7, a total of seven. The explanatory variables of the model are commercial network agglomeration scale, commercial network agglomeration density, commercial network distribution range, commercial network spatial distribution direction, etc. B1-B4 total 4. The four explanatory variables can better illustrate how the evolution of commercial space around Line 1 of Zhengzhou Metro is affected by the digital economy.

Table 3: Variables selected for the model

Variable nature	Variable name	Variable number
Explanatory variable	Platform economy	A1
	Sharing economy	A2
	Mobile payment	A3
	3R industries (Virtual reality, Augmented reality and Mixed reality)	A4
	Quadruple innovation model (Crowdsourcing, Crowdsourcing, Crowd support, Crowdfunding)	A5
	Artificial intelligence application	A6
	Blockchain application	A7
Dependent variable	Commercial outlet clustering scale	B1
	Commercial outlet clustering density	B2
	Commercial outlet distribution range	B3
	Commercial outlet spatial distribution direction	B4

3.2 Panel model definition and model selection theory

3.2.1 Panel model definition

Panel data model definition: panel data (PD) also known as “parallel data”, panel data with both time and cross-section of two dimensions, is selected in the time series of multiple cross-section, while in each cross-section of the sample observations selected by the structure of the data. The general linear panel data model is: $y_{it} = \alpha_{it} + X'_{it}\beta_{it} + \varepsilon_{it}$, $i = 1, 2 \cdots N$; $t = 1, 2 \cdots T$

where y_{it} is the dependent variable, α_{it} is the intercept term, X_{it} is a column vector of order $K \times 1$, β_{it} is a column vector of coefficients of order $K \times 1$, ε_{it} is the amount of random error, and k is the number of explanatory variables.

3.2.2 Panel data model selection process

The Mixed Model, Fixed Model, and Random Model are the three models of panel data modeling. As shown in Figure 3, three models are created separately and analyzed separately using the F test and Hausman test to determine which panel data model best fits our data set.

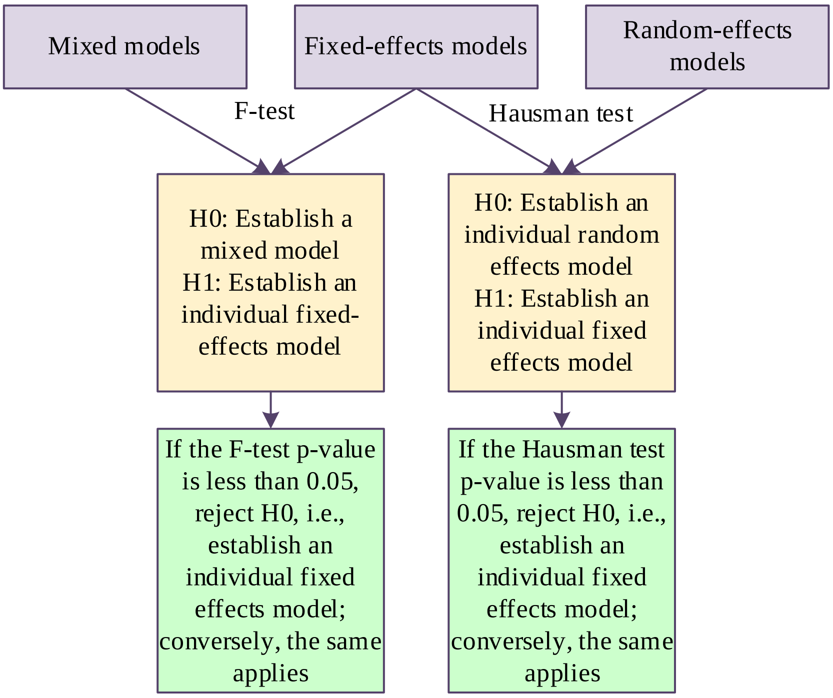


Figure 3: Panel data model determination process

3.2.3 Introduction to Mixed-Effects, Fixed-Effects, and Random-Effects Models

A mixed effects model is defined as one in which there is neither a significant difference in the data at various times with regard to time nor a significant difference in the people at the same time with respect to cross-section. That is, the mixed model is: $y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it}$, $i = 1, 2 \cdots N$; $t = 1, 2 \cdots T$

where y_{it} is the dependent variable, β_0 is the intercept term, x_{kit} is the independent variable, β_k is the coefficient term, ε_{it} is the amount of random error, and k is the number of explanatory variables.

Definition of fixed-effects model: individual fixed-effects models, time fixed-effects models, and individual-time fixed-effects models are the three general categories of fixed-effects models. The data used in this study are based on a brief period of time—less time than the total number of participants. Therefore, it would be acceptable to design an individual fixed-effects model. Definition of an individual fixed-effects model: An individual fixed-effects model is one that has distinct intercepts for every individual, i.e., $y_{it} = \alpha_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it}$, $i = 1, 2 \cdots N$; $t = 1, 2 \cdots T$

where: y_{it} is the dependent variable, α_i is the intercept term corresponding to the i th individual, which does not vary over time; x_{kit} is the independent variable; β_k is the coefficient term; ε_{it} is the random error; k is the number of explanatory variables.

Definition of Random Effects Model: The structure of the random effects model is identical to that of the fixed effects model, and the intercept term in the random effects model is independent of each person. That is, the random effects model: $y_{it} = \alpha_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it}$, $i = 1, 2 \cdots N$; $t = 1, 2 \cdots T$

where: y_{it} is the dependent variable, α_i is a random variable and its distribution is uncorrelated with x_{kit}, x_{kit} is the independent variable, β_k is the coefficient term, ε_{it} is the random error, and k is the number of explanatory variables.

3.2.4 Principles of F-test and Hausman test for panel data

The F test is conducted on sample data to determine whether the panel model should be specified as a mixed-effects model or a fixed-effects model. The corresponding F statistic is:

$$F = \frac{(SSE_m - SSE_f)/[(NT-k-1)-(NT-N-k)]}{SSE_f/(NT-N-k)} = \frac{(SSE_m - SSE_f)/(N-1)}{SSE_f/(NT-N-k)} \tag{11}$$

where SSE_m denotes the residual sum of squares under the mixed-effects model, while SSE_f denotes the residual sum of squares from the individual fixed-effects model. The F statistic therefore follows $F \sim F(N-1, NT-N-k)$, and the hypotheses are defined as follows:

H_0: intercept terms do not differ across individuals, which implies that the mixed-effects specification is appropriate;

H_1: intercept terms vary across individuals, indicating that the individual fixed-effects specification should be adopted.

The Hausman test is then used to judge whether the data support an individual fixed-effects model or a random-effects model. Its hypotheses are stated as:

H_0: individual effects are not correlated with the explanatory variables, suggesting that the random-effects model is appropriate;

H_1: individual effects are correlated with the explanatory variables, which means the individual fixed-effects model should be chosen.

3.3 Setting tests of the model form

3.3.1 F-statistics test LM test

After the sample data on the changing characteristics of commercial space around stations on Zhengzhou Metro Line 1 and the digital economy were assembled, regression analysis was carried out to identify the most suitable panel-data specification. The F test was mainly applied to compare the pooled model with the mixed model and the mixed model with the fixed-effects model. Table 4 reports the residual sum of squares for the time fixed-effects model, the individual fixed-effects model, the mixed model, and the two-way fixed-effects model. The reported values are 3.594 for the mixed model, 2.168 for the individual fixed-effects model, 2.072 for the time fixed-effects model, and 2.573 for the two-way fixed-effects model.

For F_1, which compares the mixed model with the individual fixed-effects model, the p-value is 0.03, below the 0.05 threshold. This allows rejection of the null hypothesis, indicating that the individual fixed-effects model performs better than the mixed model. For F_3, which compares the mixed model with the time fixed-effects model, the p-value is 0.02, again lower than 0.05. These p-values imply that the null hypotheses associated with the pooled model should be rejected. Therefore, all three fixed-effects specifications are accepted, while the mixed model is not retained.

Table 4: Sum of squared residuals of the 4-class model

Model	Sum of Squared Residuals
Mixed model	3.594
Individual fixed effect model	2.168
Time fixed effect model	2.072
Individual time fixed effect model	2.573

3.3.2 Hausman test

To choose between the fixed-effects model and the random-effects model, a Hausman test is carried out. This test compares the individual fixed-effects model, the time fixed-effects model, and the two-way fixed-effects model with the random-effects model, as shown in Table 5. The null hypothesis is rejected, so the fixed-effects specification is preferred, because the p-values for the comparisons between the three fixed-effects models and the random-effects model are all below 0.05. Moreover, the individual fixed-effects model is ultimately selected, since the p-value for its comparison with the random-effects model is 0.01, which is the smallest among the three cases.

Table 5: Hausman test results of the fixed model and the random model

Model combination	P-value
Individual fixed effect model & Random effects model	0.01
Time fixed effect model & Random effects model	0.04
Individual time fixed effect model & Random effects model	0.03

3.3.3 Heteroscedasticity and Autocorrelation Tests

Heteroscedasticity and autocorrelation are examined by means of the Wald test and the Friedman, Frees, and Pesaran tests, respectively, so as to reduce the possible influence of omitted variables or data differences on parameter validity. The heteroscedasticity test is built on the null hypothesis that the variances of the disturbance terms are identical across individuals, while the Wald test is carried out under the hypothesis $H_0:g(\beta)=C$, which assumes that if the constraints are true, $g(\beta^{MLE})-C\rightarrow 0$ should not differ significantly from zero; if the constraints are invalid, then $g(\beta^{MLE})-C$ will depart significantly from zero. In that case, "between-group heteroscedasticity" is considered to exist, and the null hypothesis is rejected. The autocorrelation test is conducted under the null hypothesis of no cross-sectional correlation between groups. When the p-value is below 0.01, the related test is used to reject the null hypothesis.

The results of the autocorrelation and heteroscedasticity tests are summarized in Table 6. Because the p-value of the Wald test is below 0.01, the null hypothesis of homoscedasticity across groups is strongly rejected. Accordingly, Table 6 points to the existence of heteroscedasticity within the sample data. By contrast, the p-values of Friedman's test, Pesaran's test, and Frees' test all exceed 0.1, so the null hypothesis of cross-sectional correlation is accepted.

Table 6: Test results of heteroscedasticity and autocorrelation

Heteroscedasticity test	Wald test	Chi2(14)=5.9e+36	Prob>chi2=0.004
Autocorrelation test	Pesaran's test	Cross sectional independence=1.208	Pr=0.1605
	Friedman's test	Cross sectional independence=4.576	Pr=0.8671
	Frees's test	Cross sectional independence=-0.043	Critical values from Free's Q distribution Alpha=0.15:0.2438 Alpha=0.05:0.7645 Alpha=0.01:1.9801

3.4 Regression results and analysis

Taking the outcomes of the three tests above into account, the final specification is determined as an individual fixed-effects model. Since heteroscedasticity is detected across groups in the sample, generalized least squares (GLS) estimation is introduced, and the results are presented in Table 7. The regression results for the effects of digital-economy-related variables on the evolution of commercial space around Zhengzhou Metro Line 4 are also reported there. According to the estimates, the p-value of variable 4 (3R industry, namely virtual reality, augmented reality, and mixed reality) is 0.7419, and its coefficient estimate is not statistically significant. This indicates that, during the sample period, the growth of commercial space around stations on Zhengzhou Metro Line 1 was not substantially affected by the 3R industry. A likely reason is that the development of this sector over the past decade remains constrained by the current state of physical technology, which has prevented it from making a significant contribution to commercial spatial growth.

Table 7: Regression result of evolution of commercial space in digital economy

Explain variable names	Regression coefficient	Standard error	T	P
Constant term	-126.83287	31.04108	-4.31059	0.0031
A1	9.06512	3.41292	1.77292	0.0145
A2	5.95643	2.59166	2.44953	0.0307
A3	0.56542	0.45936	5.08395	0.0053
A4	-4.07581	1.25047	-4.50222	0.7419
A5	1.90132	1.33438	0.66425	0.0024
A6	1.37021	0.67091	2.07501	0.0486
A7	5.40978	4.96017	3.28645	0.0041
R-squared	0.89978	--	--	--
Adjusted R-squared	0.86472	--	--	--

Table 8 displays the regression results of the model equation following the removal of the inconsequential variable A4, re-regression, and analysis of the equation model. According to the equation's fitness, the F-statistic of the equation satisfies P=0.00004<0.01 and the fitness index reaches 0.86472, indicating that the model equation developed in this paper fits well and can more effectively explain the primary influencing factors of the characteristics of the evolution of the commercial space in the vicinity of the Zhengzhou Metro Line 1 transportation station. Considering the significance of the explanatory variable itself, Platform Economy A1, Sharing Economy A2, Mobile Payment A3 have significant impact on the scale of commercial outlet agglomeration, density of commercial outlet agglomeration, range of commercial outlet distribution, and the spatial direction of commercial outlet distribution in the surrounding areas of the transportation station of Zhengzhou Metro Line 1 at the 0.001 level. Four Crowd Mode (crowdsourcing, crowdsourcing, crowdsourcing, crowdsourcing) A5, Artificial Intelligence Application A6, and Blockchain Application A7 have significant impact on the scale of commercial outlet agglomeration, density of commercial outlet agglomeration, range of commercial outlet distribution, and the spatial direction of commercial outlet distribution around the traffic stations of Zhengzhou Metro Line 1 at the 0.05 level.

Table 8: Regression results after eliminating the insignificant variables

Explain variable names	Regression coefficient	Standard error	T	P
Constant term	-123.81685	30.03418	-4.36537	0.0029
A1	10.06545	2.43469	1.77536	0.00012
A2	8.95463	2.59153	2.75271	0.00008
A3	8.56544	0.45466	5.78956	0.00005
A5	3.90451	0.35618	0.66523	0.0324
A6	3.32546	0.45327	2.75180	0.0417
A7	4.40532	4.56316	3.65132	0.0445
R-squared	0.89978	--	--	--
Adjusted R-squared	0.86472	--	--	--
F-statistic	295.69451	--	--	--
Prob(F-statistic)	0.00004	--	--	--

4 Conclusion

This paper develops a regression equation linking the digital economy with the changing pattern of commercial space around stations on Zhengzhou Metro Line 1, with the aim of identifying which digital-economy factors influence spatial development patterns. Among the seven explanatory variables representing digital-economy factors, the 3R industry (virtual reality, augmented reality, and mixed reality) has a p-value greater than 0.05 and therefore does not exert a significant influence on the transformation of the commercial-space structure considered in this study. By contrast, platform economy, the sharing economy, and mobile payment all show significant effects on the evolution of commercial space around Zhengzhou Metro Line 1 over the past decade ($P<0.001$). The remaining variables, namely the four crowds model, AI applications, and blockchain applications, are also significant at the 0.05 level, although their effects are weaker than those of the first three variables.

Judging from the results of technical exploration and the assessment of digital-economy value, the rapid growth of the platform economy, the sharing economy, mobile payment, and other digital forms has played a central role in reshaping the evolution of commercial space around stations on Zhengzhou Metro Line 1. Factors such as platform diversity and payment convenience have attracted more commercial outlets to enter the area and reorganize their spatial layout, thereby promoting prosperity in areas surrounding transport hubs.

About the Author

Guimin Ma was born in Hubei, China, in 1983. From 2001 to 2006, he studied in Wuhan University and received his bachelor's degree in 2006. From 2006 to 2009, he worked in Henan

University of Urban Construction. From 2009 to 2012, he studied in Huazhong University of Science and Technology and received his Master's degree in 2012. From 2014 to 2022, he studied in Tianjin University and received his Doctor's degree in 2022. Currently, he works in Henan University of Urban Construction. He has published more than ten papers. His main research activity is in the area of digital architectural design, transportation architecture and station planning, residential architecture and environmental design.

Jialin Hou was born in Inner Mongolia, China, in 1988. From 2008 to 2013, she studied in Henan University of Urban Construction and received her bachelor's degree in 2013. From 2014 to 2017, she studied in Beijing University of Civil Engineering and Architecture and received her Master’s degree in 2017. Currently, She is a lecturer and works at Henan University of Urban Construction. Her main research activity is in the area of digital architectural design, and residential architecture and environmental design.

References

[1] Han, F., Xie, R., & Lai, M. (2018). Traffic density, congestion externalities, and urbanization in China. Spatial Economic Analysis, 13(4), 400-421.

[2] Alama, E. T., Aloysius, A., & Ph, T. (2021). Urbanization and transportation crisis in urban centres: the Panacea. J Res Human Soc Sci, 9(6), 7-17.

[3] Yang, Y. U., Xin, T. A. N., & Yuexi, Q. I. A. N. (2018). Evolution of Commercial Space near the Subway Stations of Community Type Based on Self-Organization Theory: A Case Study of Chengdu Wannianchang Subway Station. Journal of Landscape Research, 10(4).

[4] Tang, M., Buchmeister, B., Gong, D., Xue, G., & Khoa, B. T. (2025). Subway Expansion and Traffic Flow: A Spatiotemporal Analysis of Urban Congestion Dynamics. Tehnički vjesnik, 32(1), 44-53.

[5] Yuliang, C., Ma, Y., Yanying, Y., & Rongguang, S. (2023). The impact of urban rail transit and synergistic development of urban-rural integration on rural revitalization: the case of Zhengzhou City. Journal of Agriculture Resources and Environment, 40(5), 1134.

[6] Qi, J., Niu, S., Ye, C., Wang, L., Wei, Y., Wen, Y., & Zhao, S. (2021). Identifying the geography and determinants of O2O online retailers in megacity in Central China: a case study of Zhengzhou City. Chinese Geographical Science, 31(5), 931-950.

[7] Abudurexiti, A., Abulikemu, Z., & Keyimu, M. (2025). POI-Based Assessment of Sustainable Commercial Development: Spatial Distribution Characteristics and Influencing Factors of Commercial Facilities Around Urumqi Metro Line 1 Stations. Sustainability (2071-1050), 17(12).

[8] Chang, T., Yang, D., Yang, Y., Huo, J., Wang, G., & Xiong, C. (2018). Impact of urban rail transit on business districts based on time distance: Urumqi Light Rail. Journal of Urban Planning and Development, 144(3), 04018024.

[9] Zhang, L., & Zhuang, Y. (2019). Analysis of multiple network accessibilities and commercial space use in metro station areas: An empirical case study of Shanghai, China. International Journal of High-Rise Buildings, 8(1), 49-56.

[10] Zhai, D. (2020, May). Study on the Differentiation Characteristics and Influence of Retail Commercial Space around Urban Rail Transit Stations. In 2020 5th IEEE International Conference on Big Data Analytics (ICBDA) (pp. 309-314). IEEE.

[11] Lin, D., Nelson, J. D., Beecroft, M., & Cui, J. (2023). Understanding China's metro development: A comparative regional analysis. Research in Transportation Business & Management, 47, 100940.

[12] Zhang, S., Huang, Z., & Zhao, K. (2025). Research on the Coordinated Development of "Node-Place" in Intercity Railway Station Areas: A Case Study of the Guangdong–Hong Kong–Macao Greater Bay Area, China. ISPRS International Journal of Geo-Information, 14(3), 121.

[13] Yang, Y., Jie, Y., Bo, Z., Yuexi, Q., & Guangyuan, Z. (2017). Analysis of the Development of the Commercial Space Around Metro Stations in Urban Core Areas Based on Place Making: A Case Study of Chunxi Road Metro Station in Chengdu. Journal of Landscape Research, 9(6), 7-12.

[14] Peng, J., & Peng, F. L. (2018, May). Layout patterns of underground space comprehensive utilization around metro station for urban commercial area. In GeoShanghai International Conference (pp. 587-596). Singapore: Springer Singapore.

[15] Kan, D., Lyu, L., Huang, W., & Yao, W. (2022). Digital economy and the upgrading of the global value chain of China's service industry. Journal of Theoretical and Applied Electronic Commerce Research, 17(4), 1279-1296.

[16] Song, Y., & Jiang, Y. (2024). How does the digital economy drive the optimization and upgrading of industrial structure? the mediating effect of innovation and the role of economic resilience. Sustainability, 16(4), 1352.

[17] Zhang, W., Zhao, S., Wan, X., & Yao, Y. (2021). Study on the effect of digital economy on high-quality economic development in China. PloS one, 16(9), e0257365.

[18] Meng, T., Yu, D., Ye, L., Yahya, M. H., & Zariyawati, M. A. (2023). Impact of digital city competitiveness on total factor productivity in the commercial circulation industry: evidence from China's emerging first-tier cities. Humanities and Social Sciences Communications, 10(1), 1-10.

[19] Ma, D., & Ma, Y. (2025). The impact of the digital economy on quality of life: empirical evidence from 220 cities in China. Digital Policy, Regulation and Governance, 27(4), 404-421.

[20] Shen, S., Li, H., & Li, M. (2023). Transportation infrastructure and digital economy—evidence from Chinese cities. Sustainability, 15(22), 16024.