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## **Impact of digital and intelligent human resource management on total factor productivity in agritourism integration**

Based on panel data from 138 agritourism integration projects across 23 provinces in China, this paper investigates the productivity drivers of the industry. Data Envelopment Analysis and the Malmquist Productivity Index were employed to calculate Total Factor Productivity. Using the entropy method, a comprehensive index was constructed to evaluate the level of digitalisation and intelligensation of Human Resource Management. The study establishes a statistically significant positive impact of digital HRM transformation on TFP dynamics. It was found that capital allocation efficiency and labour allocation efficiency act as partial mediators, accounting for 29.9 % and 36.6 % of the total effect, respectively. A regional gradient was identified, with the most pronounced impact observed in the eastern regions of China.

*Keywords:* agritourism in China, digital transformation, human resource management, total factor productivity, Malmquist index.

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## **Исследование влияния цифрового и интеллектуального управления человеческими ресурсами на совокупную факторную производительность в интеграции агротуризма**

На основе панельных данных по 138 проектам интеграции агротуризма в 23 провинциях Китая проведено исследование факторов производительности отрасли. С применением метода анализа оболочки и индекса производительности Мальмквиста рассчитана совокупная факторная производительность. С помощью метода энтропии сформирован комплексный индекс оценки уровня цифровизации и интеллектуализации управления человеческими ресурсами. Установлено статистически значимое положительное влияние цифровой трансформации HR-менеджмента на динамику совокупной факторной производительности. Выявлено, что эффективность распределения капитала и трудовых ресурсов выступает в качестве частичных медиаторов, объясняя 29,9 % и 36,6 % общего эффекта соответственно. Определен региональный градиент: наибольший эффект зафиксирован в восточных регионах КНР.

*Ключевые слова:* агротуризм в Китае, цифровая трансформация, управление человеческими ресурсами, совокупная факторная производительность, индекс Мальмквиста.

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## Introduction

At present, technologies such as big data and artificial intelligence are rapidly permeating various industries, driving the digital and intelligent transformation of business management. As a key component of this transformation, the digital and intelligent transformation of human resources utilises technological means to unlock workforce potential and optimise resource allocation, thereby enabling dynamic, real-time human resources management [1]. This transformation not only affects the manufacturing and service sectors but also offers new avenues for improving efficiency in the integration of agriculture and tourism against the backdrop of rural revitalisation [2].

The integration of agriculture and tourism is a rural development model that China has been actively promoting in recent years, with the aim of revitalising the agricultural economy, increasing farmers' incomes and stimulating consumption. However, traditional agritourism, which primarily takes the form of fruit picking, farm stays and folk performances, is generally characterised by small scale and limited variety, posing challenges to the sustainability of such projects [3]. Against this backdrop, the development of integrated agriculture, culture and tourism complexes has emerged as a key pathway for rural revitalisation. In practice, agricultural, cultural and tourism complexes across various provinces are often led by asset management platforms under municipal and county financial authorities, with private enterprises brought in to manage day-to-day operations. Once projects enter the operational phase, they typically conduct business as standard enterprises [4].

How can the efficiency of such commercially operated agritourism projects be assessed? Total factor productivity provides a suitable measurement tool. This indicator filters out the simple growth in factor inputs such as capital, land and labour, focusing instead on output gains resulting from technological progress, optimised resource allocation and management innovation; it is therefore well-suited to evaluating the impact of digital and intelligent human resource management on the efficiency of agritourism integration. Accordingly, this paper examines the relationship between the digitalisation and intelligentisation of human resources and the total factor productivity of agritourism integration, exploring its mechanisms and regional variations to provide empirical evidence for enhancing the efficiency of the agritourism industry.

## Main Part

This study primarily employs an empirical research approach, supplemented by literature analysis to strengthen the theoretical foundation.

The panel data used in this study are sourced from provincial statistical yearbooks, government portals, project websites and interviews [5]. The sample covers 23 provinces nationwide, comprising 138 agritourism integration projects, of which 50 are

in the eastern region, 45 in the central region and 43 in the western region. Samples with missing indicators were excluded during the statistical analysis phase to ensure data integrity. For subjective indicators, such as the level of policy support obtained through interviews, data reliability was ensured by employing independent scoring by two assessors and calculating the coefficient of consistency.

**Dependent variable:** Total Factor Productivity (TFP) of agritourism integration. This study employs the DEA-based Malmquist index method for calculation. The output indicator selected is the annual operating revenue (in 10,000 CNY) of each agritourism project; input indicators include: capital input (net fixed assets, in 10,000 CNY), labour input (number of employees at year-end, in persons), and land input (project land area, in mu). Using 2019 as the base year, the annual total factor productivity change index for each project was calculated.

**Explanatory variable:** Level of digitalisation in human resources (HRD). This study constructs a comprehensive evaluation indicator system based on three dimensions: Digital infrastructure (whether an HR management system is in place, and network bandwidth conditions); Digital talent pool (proportion of staff with a college degree or higher, and proportion of IT personnel); Depth of digital application (coverage of online training, and proportion of HR processes conducted online). Data is sourced from the annual reports of project enterprises, internal management systems, and interview surveys. The entropy method is employed for objective weighting to synthesise a comprehensive index of HR digitalisation for each project, with values ranging from 0 to 1; a higher value indicates a higher level of digitalisation.

**Intermediate variables.** Capital Allocation Efficiency (CAE) is measured by the capital-output ratio, i.e. the operating revenue generated per unit of capital input; a higher value indicates greater capital allocation efficiency. Labour allocation efficiency (LAE) is measured by the labour-output ratio, i.e. the operating revenue generated per unit of labour input; a higher value indicates greater labour allocation efficiency. Land allocation efficiency (TAE) is measured by the land-output ratio, i.e. the operating revenue generated per unit of land area; a higher value indicates greater land allocation efficiency.

**Control variables.** Per capita GDP (PCGDP, 10,000 CNY/person) is selected to measure the level of regional economic development; road density (RDD, km/km<sup>2</sup>), to measure transport infrastructure conditions; policy support intensity (PSS), obtained by text-based quantification and scoring of the number of specialised agritourism integration policies and the amount of fiscal subsidies introduced in the regions where the projects are located, with values ranging from 0 to 0.1; and the proportion of the agritourism workforce (AER), measured as the ratio of the number of people employed in the agritourism industry in the county where the project is located to the total number of employed persons in the county. Table 1 presents the descriptive statistics for the main variables.

Table 1. Descriptive Statistics

Variable name	Symbol	Observed value	Mean	Standard deviation	Minimum value	Maximum value
Total Factor Productivity of Agritourism Integration	TFP	138	1.023	0.215	0.689	1.567
Level of Digitalisation and Intelligence in Human Resources	HRD		0.387	0.124	0.156	0.698
Efficiency of Capital Allocation	CAE		0.452	0.103	0.231	0.724
Efficiency of Labour Allocation	LAE		5.892	1.347	3.215	8.763
Efficiency of Land Allocation	TAE		3.674	0.982	1.897	5.981
GDP per Capita	PCGDP		7.654	2.138	4.231	12.897
Road Density	RDD		0.876	0.321	0.345	1.567
Level of Policy Support	PSS		0.032	0.015	0.008	0.076
Proportion of the Workforce Employed in the Agritourism Sector	AER		0.125	0.043	0.056	0.231

Note. It compiled based on the results of our own research.

The mean total factor productivity (TFP) of agritourism integration was 1.023, slightly above 1, indicating that, during the sample period, China’s agritourism integration industry as a whole was in a phase of efficiency improvement. The standard deviation was 0.215, with a range of 0.878 between the minimum and maximum values, demonstrating significant differences in the quality of development across different regions. The mean value of the Human Resource Digitalisation Level (HRD) was 0.387, with a standard deviation of 0.124 and a range of 0.156 to 0.698, reflecting that the development of human resource digitalisation across provinces was at a moderate level, with uneven progress across regions. The mean value for capital allocation efficiency (CAE) is 0.452, indicating that each unit of capital investment generates 0.452 CNY in operating revenue; the mean value for labour allocation efficiency (LAE) is 5.892, indicating that each unit of labour input generates 58,920 CNY in operating revenue; and the mean value for land allocation efficiency (TAE) is 3.674, indicating that each unit of land input generates 36,740 CNY in operating revenue. No concentration of extreme values was observed in the standard deviations of these three indicators. The mean Policy Support Strength (PSS) was 0.032, with a significant gap between the minimum and maximum values, indicating a marked divergence in the level of policy support across different regions.

To provide an initial assessment of the relationships between variables, Table 2 presents the results of the Pearson correlation analysis for the main variables. The correlation coefficient between the independent variable HRD and the dependent variable TFP is 0.523, and is significant at the 1 % level, indicating a strong positive associa-

tion between the digitalisation of human resources and the total factor productivity of agritourism integration. The correlation coefficients between the mediating variables CAE, LAE, and TFP were 0.412 and 0.456 respectively, both showing a significant positive correlation at the 1 % level, suggesting that both may have a promotional effect on TFP. The correlation coefficient between TAE and TFP was 0.178 and was not significant; its role requires further verification. The correlation coefficients between HRD and CAE, and between HRD and LAE, were 0.387 and 0.432 respectively, both significant at the 1 % level, suggesting that the digitalisation of human resources might influence TFP by optimising the efficiency of capital and labour allocation.

Table 2. Correlation Analysis

Variable	TFP	HRD	CAE	LAE	TAE	PCGDP	RDD	PSS	AER
TFP	1.000								
HRD	0.523***	1.000							
CAE	0.412***	0.387***	1.000						
LAE	0.456***	0.432***	0.367**	1.000					
TAE	0.178	0.145	0.192	0.213	1.000				
PCGDP	0.289**	0.234*	0.201	0.256*	0.121	1.000			
RDD	0.103	0.089	0.112	0.134	0.097	0.245*	1.000		
PSS	0.321***	0.278**	0.223*	0.267**	0.156	0.298**	0.189	1.000	
AER	0.135	0.117	0.142	0.168	0.109	0.187	0.123	0.176	1.000

\*, \*\* and \*\*\* denote significance at the 10 %, 5 % and 1 % levels, respectively.

Notes:

1. Blank cells indicate that the variable was not included in the corresponding model specification.
2. It compiled based on the results of our own research.

Among the control variables, PCGDP and PSS were significantly positively correlated with TFP at the 5 % and 1 % levels respectively, indicating that the level of regional economic development and the intensity of policy support have a positive impact on TFP. The correlations between RDD, AER and TFP did not pass the significance test. Overall, the absolute values of the correlation coefficients between all variables were less than 0.6, and the variance inflation factors (VIF) were all less than 3, indicating that there were no serious issues of multicollinearity.

To examine the baseline effect of digital and intelligent human resource management on the total factor productivity of agritourism integration, Table 3 employs a stepwise method of adding control variables to conduct a fixed-effects regression. Column (1) includes only HRD, with a coefficient of 0.587 that is significant at the 1 % level, providing preliminary evidence of the promotional effect of digital and intelligent human resource development. In Column (2), following the inclusion of PCGDP, the HRD coefficient decreases to 0.543 (significant at the 1 % level), whilst the PCGDP coefficient is 0.092 (significant at the 5 % level). This indicates that improvements in regional economic development can provide better technical and financial support for agritourism integration, thereby promoting an increase in total factor productivity.

In Column (3), following the inclusion of RDD, the HRD coefficient decreased slightly to 0.521 (significant at the 1 % level), whilst the RDD coefficient was not significant. Possible reasons for this include the fact that, as a modern service industry, the efficiency gains of agritourism integration rely more heavily on digital management and service innovation, with the marginal contribution of traditional transport infrastructure having entered a plateau phase; simultaneously, the impact of RDD may be exerted indirectly through channels such as digital infrastructure. In Column (4), after incorporating PSS, the coefficient stands at 1.213 (significant at the 1 % level), indicating that policy support exerts a strong positive incentive effect on the total factor productivity of agritourism integration; measures such as fiscal subsidies and policy guidance can effectively reduce operating costs and optimise resource allocation. At this point, the HRD coefficient is 0.489 (significant at the 1 % level), suggesting that the promotional effect of digital and intelligent human resource management remains robust even after controlling for policy support. In Column (5), after incorporating all control variables, the model's R<sup>2</sup> increases to 0.458, and the HRD coefficient stands at 0.492 (significant at the 1 % level), further validating the robust promotional effect of the digitalisation and intelligentisation of human resources. The AER coefficient is 0.452 and is not significant; this may be because the mere growth in the number of employees in the agritourism industry has not led to a corresponding increase in skill levels, and the scale effects of labour force expansion have not yet been fully translated into efficiency gains.

**Table 3. Baseline Regression**

Dependent variable: TFP	(1)	(2)	(3)	(4)	(5)
HRD	0.587*** (3.892)	0.543*** (3.678)	0.521*** (3.456)	0.489*** (3.312)	0.492*** (3.215)
PCGDP		0.092** (2.134)	0.091** (2.098)	0.089** (2.056)	0.089** (2.013)
RDD			0.036 (1.289)	0.035 (1.254)	0.034 (1.237)
PSS				1.213*** (2.934)	1.235*** (2.987)
AER					0.452 (1.562)
Constant term	0.765*** (4.123)	0.412*** (3.012)	0.389** (2.567)	0.345** (2.345)	0.321** (2.145)
Individual fixed	Yes	Yes	Yes	Yes	Yes
N	138	138	138	138	138
R <sup>2</sup>	0.326	0.378	0.392	0.435	0.458
F-value	15.143***	16.892***	17.234***	18.123***	18.762***

\*\* and \*\*\* denote significance at the 10 %, 5 % and 1 % levels, respectively.

Notes:

1. The figures in brackets are t-values.
2. Blank cells indicate that the variable was not included in the corresponding model specification.
3. It compiled based on the results of our own research.

Following the procedure for testing mediating effects outlined by Wen Zhonglin et al. (2014), this section employs a three-step regression analysis to verify the mediating roles of capital allocation efficiency (CAE), labour allocation efficiency (LAE) and land allocation efficiency (TAE) [6].

The Impact of Digitalisation of Human Resources on Mediating Variables. Table 4 shows that the regression coefficient of HRD on CAE is 0.321 (significant at the 1 % level), indicating that the digitalisation and intelligentisation of human resources helps to optimise capital allocation, reduce inefficient capital utilisation, and enhance capital allocation efficiency. The coefficient of HRD on LAE is 0.897 (significant at the 1 % level), suggesting that the digitalisation and intelligentisation of human resources can improve the match between labour and job roles through digitalised skills training and intelligent talent matching, thereby enhancing labour allocation efficiency. The coefficient of HRD on TAE is 0.215 and is not significant. This may be due to the immovable nature of land resources and the rigidity of planning, as well as constraints imposed by external factors such as land policies and spatial planning, making it difficult for the impact of digitalisation and intelligentisation to manifest in the short term.

Table 4. Regression of HRD on Mediating Variables

Dependent variable	CAE	LAE	TAE
HRD	0.321*** (3.145)	0.897*** (3.567)	0.215 (1.432)
Control variables	Yes	Yes	Yes
Constant term	0.234** (2.098)	3.456*** (4.231)	2.897*** (3.876)
N	138	138	138
R <sup>2</sup>	0.389	0.421	0.213
F-value	16.892***	17.563***	8.921**

\*\* and \*\*\* denote significance at the 5 % and 1 % levels, respectively.

Notes:

1. The figures in brackets are t-values.
2. It compiled based on the results of our own research.

Testing the mediating effects of the mediating variables. Table 5 reports the regression results after simultaneously including HRD and the mediating variables. In Column (1), following the inclusion of CAE, the HRD coefficient decreased from 0.492 in the baseline regression to 0.345 (significant at the 1 % level), whilst the CAE coefficient was 0.321 (significant at the 5 % level). This indicates that capital allocation efficiency plays a partial mediating role, with the proportion of the mediating effect being approximately  $(0.492 - 0.345) / 0.492 \approx 29.9\%$ . In Column (2), after including LAE, the HRD coefficient fell to 0.312 (significant at the 1 % level), whilst the LAE co-

efficient was 0.045 (significant at the 5 % level). Labour allocation efficiency likewise played a partial mediating role, with the proportion of the effect estimated at  $(0.492 - 0.312) / 0.492 \approx 36.6\%$ . In Column (3), after including TAE, the HRD coefficient is 0.478 (significant at the 1 % level), whilst the TAE coefficient is not significant, confirming that land allocation efficiency does not play a mediating role. In Column (4), after incorporating all three mediating variables, the HRD coefficient is 0.289 (significant at the 1 % level), with the CAE and LAE coefficients at 0.287 (significant at the 5 % level) and 0.038 (significant at the 10 % level) respectively, whilst TAE remains insignificant. These results indicate that the digitalisation of human resources primarily promotes the improvement of total factor productivity in agritourism integration through two pathways: optimising capital allocation efficiency and labour allocation efficiency, whilst land allocation efficiency does not form an effective transmission mechanism.

Table 5. Regression of HRD and Mediating Variables on TFP

Dependent variable: TFP	(1)	(2)	(3)	(4)
HRD	0.345*** (2.987)	0.312*** (2.876)	0.478*** (3.109)	0.289*** (2.654)
CAE	0.321** (2.134)			0.287** (2.012)
LAE		0.045** (2.056)		0.038* (1.897)
TAE			0.021 (1.123)	0.018 (1.098)
Control variable	Yes	Yes	Yes	Yes
Constant term	0.213* (1.892)	0.198* (1.789)	0.298** (2.034)	0.176 (1.567)
N	138	138	138	138
R <sup>2</sup>	0.412	0.435	0.461	0.513
F-value	17.982***	18.345***	17.891***	20.123***

\*, \*\* and \*\*\* denote significance at the 10 %, 5 % and 1 % levels, respectively.

Notes:

1. The figures in brackets are t-values.
2. Blank cells indicate that the variable was not included in the corresponding model specification.
3. It compiled based on the results of our own research.

Test for Regional Heterogeneity. Given the significant differences between the eastern, central and western regions in terms of digital infrastructure, economic development levels and the maturity of the agritourism industry, this section divides the sample into three major regions to conduct a test for heterogeneity. The results are shown in Table 6.

Table 6. Test of Regional Heterogeneity

Dependent variable: TFP	Eastern	Central	Western
HRD	0.621*** (3.987)	0.389** (2.234)	0.198 (1.345)
Control variable	Yes	Yes	Yes
Constant term	0.289** (2.145)	0.356** (2.098)	0.412* (1.765)
N	50	45	43
R <sup>2</sup>	0.523	0.398	0.235
F-value	21.345***	15.678***	7.892**

\*, \*\* and \*\*\* indicate significance at the 10 %, 5 % and 1 % levels, respectively.

Notes:

1. The figures in brackets are t-values.
2. It compiled based on the results of our own research.

The HRD coefficient for the eastern region is 0.621 (significant at the 1 % level), the highest among the three regions, with an R<sup>2</sup> of 0.523, indicating the best model fit. This result suggests that the eastern region, with its well-developed digital infrastructure and ample talent pool, demonstrates greater compatibility between the digitalisation of human resources and agritourism integration, thereby enabling it to more fully leverage efficiency gains. The HRD coefficient for the Central Region is 0.389 (significant at the 5 % level), which is lower than that of the Eastern Region, with an R<sup>2</sup> of 0.398. This is primarily because traditional business models dominate the agritourism industry in the Central Region, and digital transformation is in its infancy. Constrained by factors such as technology and funding, the promotional effects of digital and intelligent human resource management have not been fully realised. The HRD coefficient for the Western Region is 0.198 and is not statistically significant, with an R<sup>2</sup> of only 0.235. Possible reasons include the region’s weak digital infrastructure and shortage of specialised technical personnel. The agritourism sector in the Western Region is predominantly characterised by small-scale, extensive operations, with limited application scenarios for digital and intelligent human resource management, failing to form effective synergies with local agricultural and tourism resources. Overall, the promotional effect of digital and intelligent human resource management on the total factor productivity of agritourism integration exhibits a regional gradient pattern of Eastern > Central > Western.

Robustness Tests. To ensure the reliability of the core findings, this study conducted robustness tests using three methods, with the results shown in Table 7.

Table 7. Robustness Tests

Test methods	HRD Coefficient	t-value	N	R <sup>2</sup>
Replace the dependent variable	0.476***	3.123	138	0.432
Truncate to the nearest 1 %	0.501***	3.098	138	0.445
Exclude outliers (top 5 % by revenue)	0.483***	2.987	131	0.428

\*\*\* denote significance at the 1 % levels, respectively.

Note. It compiled based on the results of our own research.

First, the dependent variable was replaced. The total factor productivity of agritourism integration (TFP\_CRS) was recalculated using the DEA-CRS model to avoid potential biases arising from a single estimation method. The regression results showed that the HRD coefficient was 0.476 (significant at the 1 % level), which close to the 0.492 is obtained in the baseline regression, indicating that the core conclusions are not affected by the estimation method of the dependent variable.

Second, 1 % truncation. To address potential interference from outliers, all continuous variables were subjected to two-sided truncation at the 1 % quantile to eliminate the influence of outliers. Following this treatment, the HRD coefficient was 0.501 (significant at the 1 % level), showing little difference from the baseline result, indicating that outliers did not have a substantial impact on the core conclusions.

Third, removal of outliers. To account for potential estimation bias arising from abnormally high revenue scales in some agritourism projects, samples in the top 5 % by revenue scale were excluded and the regression was rerun. The HRD coefficient was 0.483 (significant at the 1 % level), with a model  $R^2$  of 0.428, consistent with the baseline regression results.

The results of all three tests indicate that the positive impact of digitalisation of human resources on the total factor productivity of agritourism integration is robust and is not affected by estimation methods, outliers or anomalous samples.

## **Conclusions**

Based on panel data from 138 agritourism integration projects, this study empirically analyses the impact of digitalisation and intelligentisation of human resources on the total factor productivity of agritourism integration, as well as its underlying mechanisms. The main conclusions are as follows:

First, the digitalisation and intelligentisation of human resources have a significant positive impact on the total factor productivity of agritourism integration. The results of the baseline regression show that, after progressively incorporating control variables, the HRD coefficient remains significantly positive at the 1 % level, indicating that improvements in the level of digitalisation and intelligence of human resources can effectively drive efficiency gains in agritourism integration.

Second, mechanism tests indicate that capital allocation efficiency and labour allocation efficiency play a partial mediating role between the digitalisation and intelligence of human resources and the total factor productivity of agritourism integration, with mediation effects accounting for approximately 29.9 % and 36.6 % respectively. The digitalisation and intelligentisation of human resources indirectly promote the improvement of total factor productivity by optimising capital allocation and enhancing the match between labour and job roles. The mediating effect of land allocation efficiency is not significant, possibly due to constraints imposed by the inherent characteristics of land resources.

Thirdly, the promotional effect exhibits significant regional heterogeneity. The eastern region exhibits the strongest positive effect of digitalisation of human resources,

owing to its well-developed digital infrastructure and ample talent pool; the central region, being in the early stages of digital transformation and constrained by technology and funding, shows a relatively weaker effect; whilst the western region, due to its weak digital foundation and shortage of specialized talent, fails to pass the significance test for this effect. The identified regional gradient, following the ‘East-Central-West’ trajectory, is consistent with the fundamental disparities in China’s regional economic development. Fourthly, following multiple robustness tests including substituting the dependent variable, truncation, and the removal of outliers the core conclusions remain significant, indicating a high degree of reliability in the research findings.

Based on the above conclusions, this paper proposes the following policy recommendations: Firstly, accelerate the digital and intelligent transformation of human resources in agritourism integration projects, encouraging enterprises to adopt digital management systems to enhance talent matching efficiency; secondly, to implement differentiated policies for the eastern, central and western regions: the eastern region should focus on deepening collaborative innovation between digitalisation and agritourism integration; the central region should increase technical and financial support to drive digital transformation; and the western region should prioritise the improvement of digital infrastructure; thirdly, to optimise the allocation of capital and labour, leveraging the enabling role of digitalisation in factor allocation; and fourthly, to continuously strengthen policy support by using tools such as fiscal subsidies and tax incentives to reduce the operational costs of agritourism projects and stimulate the vitality of market entities.

#### REFERENCES

1. Li Guoli. Enterprise Information Transformation under the Empowerment of Artificial Intelligence: Research on Management Change Path and Practice Mechanism / Li Guoli // *E-Commerce Letters*. – 2025. – Vol. 14. – P. 6696. <https://doi.org/10.12677/ecl.2025.14124663>.
2. Lian Hongping. Empirical Research on the Integrated Development of Rural Industries Empowered by Digital Economy / Lian Hongping, Han Wenjing // *Studies on Socialism with Chinese Characteristics*. – 2025. – Vol. 7, № 1. – P. 55–66.
3. Li M. Agricultural-Tourism Integration Development Mode and Path Optimization under the Background of Rural Revitalization: Reflection on the Integration Development of Rural Industries / Li M., Wang X. // *Guizhou Social Sciences*. – 2022. – № 3. – P. 153–159.
4. How Do Multiple Subjects Promote the High-Quality Development of Rural Tourism from the Perspective of New Endogenous Development Theory? An Empirical Study Based on a Sample of 16 Villages in 8 Cities of Zhejiang Province / Li Qiucheng, Liu Xin, Guan Jingjing [et al.] // *Tourism Tribune*. – 2025. – № 1. – P. 12–28.
5. Li Gil-Lian. Research on the Integrated Development of Agriculture, Culture and Tourism in China: A Case Study of Henan Province / Li Gil-Lian, Liu Zhou // *Asian Studies*. – 2025. – Vol. 28, № 4. – P. 603–619.
6. Wen Zhonglin. Mediation Effects Analysis: Methods and Model Development / Wen Zhonglin, Ye Baojuan // *Advances in Psychological Science*. – 2014. – Vol. 22, № 5. – P. 731–745. <https://doi.org/10.3724/SP.J.1042.2014.00731>.

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