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Nonlinear Effects of Digital Inclusive Finance on Urban–Rural Income Gap in Northwest China

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Abstract— With the rapid development of digital technology, digital inclusive finance has gradually become an important tool for promoting economic development and reducing income disparities. This paper takes the northwest region of China as the research object and uses panel data from 2014 to 2023 to analyze the impact of digital inclusive finance on the urban–rural income gap. Based on theoretical analysis, a panel data model is constructed, and the nonlinear relationship between digital inclusive finance and the urban–rural income gap is further examined. Through empirical analysis of relevant variables, the study explores the mechanism through which changes in the level of digital inclusive finance affect the urban–rural income gap. The research helps to deepen the understanding of the economic effects of digital inclusive finance and provides a reference for promoting regional coordinated development and optimizing digital financial policies.

Keywords: Digital inclusive finance, Urban rural income Gap; Panel data model; Nonlinear relationship

I. INTRODUCTION

With the rapid development of digital technology, the digital economy has become an important driving force for economic growth and social development. In recent years, China has made remarkable progress in the development of the digital economy. The integration of digital technology with financial services has promoted the emergence of digital inclusive finance, which relies on technologies such as mobile payments, big data, and the internet to provide financial services to a wider range of groups. Compared with traditional financial services, digital inclusive finance can effectively reduce the threshold and cost of financial services, improve financial accessibility, and provide more convenient financial support for small businesses and low-income groups.At the same time, income inequality remains an important issue in China’s economic development. In particular, the urban–rural income gap has long been a key concern in the process of economic growth and social development. Due to differences in economic development levels, industrial structure, and financial resource allocation, there are still significant disparities between urban and rural residents in many regions of China. Therefore, exploring effective ways to narrow the urban–rural income gap has become an important topic in both academic research and policy discussions.With the continuous development of digital inclusive finance, scholars have gradually paid attention to its potential impact on income distribution. On the one hand, digital inclusive finance can expand financial service coverage and improve financial accessibility for rural residents, which may help increase income opportunities and reduce the income gap. On the other hand, due to differences in digital infrastructure, financial literacy, and economic development levels among regions, the benefits of digital financial development may not be evenly distributed. As a result, the impact of digital inclusive finance on the urban–rural income gap may be more complex and deserves further investigation.Against this background, this study takes the northwest region of China as the research object and uses panel data from 2014 to 2023 to analyze the impact of digital inclusive finance on the urban–rural income gap. By constructing a panel data model, this paper empirically examines the relationship between digital inclusive finance and the urban–rural income gap and further explores the possible nonlinear relationship between them. The results of this study are expected to provide useful insights for promoting digital financial development and narrowing the urban–rural income gap, thereby supporting balanced regional development.

II. LITERATURE REVIEW

With the rapid integration of digital technologies into financial systems, digital inclusive finance has emerged as a key instrument for promoting inclusive growth and addressing income disparities between urban and rural areas. In recent years, a growingbody of literature has examined whether and how digital inclusive finance affects the urban–rural income gap, particularly in developing and emerging economies. However, existing studies have not reached a unanimous conclusion regarding the direction and mechanisms of this relationship. A substantial strand of the literature argues that digital inclusive finance can contribute to narrowing the urban–rural income gap by improving access to financial services, alleviating credit constraints, and enhancing income-generating opportunities for rural and low-income populations. Using Chinese provincial data, Yu and Wang (2021) find that digital inclusive finance significantly reduces the urban–rural income gap by optimizing the structure of urban and rural incomes. Gao, Wu, and Li (2024) further demonstrate that digital inclusive finance enhances rural loan availability, which promotes income growth among rural households and helps reduce urban–rural incomedisparities.Wang, Wu, and Fu (2024), focusing on China's Yangtze River Delta, find that digital inclusive finance can exert an inequality-reducing effect under favorable regional development and institutional conditions.Recent studies also emphasize the broader development context in which digital inclusive finance operates. Becha et al. (2025), employing a panel threshold model for China, reveal that digital inclusive finance promotes regional economic growth and environmental sustainability after surpassing certain development thresholds. Their findings suggest that the inclusive effects of digital finance, including its potential to mitigate income disparities, are conditional on development stages and structural characteristics. In contrast, another line of research highlights that digital inclusive finance may, under certain circumstances, exacerbate income inequality. Yao and Ma (2022) argue that digital finance can widen income gaps when benefits are disproportionately captured by urban residents and higher-income groups, particularly due to differences in digital literacy, infrastructure, and financial capability. This "digital divide" may limit the extent to which rural populations can fully benefit from digital financial services.Zhang et al. (2024) further question whether digital inclusive finance is genuinely inclusive, suggesting that insufficient regulation and institutional weaknesses may allow financial risks and fraudulent activities to disproportionately harm vulnerable groups. Their findings imply that digital finance may deviate from its inclusive objectives if governance mechanisms are inadequate. Consistent with this view, Wang, Wu, and Fu (2024) identify a dual effect of digital inclusive finance on the urban–ruralincome gap, where its impact depends on regional economic development levels and institutional environments. Beyond the Chinese context, international studies provide complementary insights into the relationship between digital finance, inequality, and development. Asongu (2024), focusing on sub-Saharan Africa, finds that mobile money innovations can reduce poverty and inequality, although the magnitude of these effects varies substantially across countries. Khera, Ogawa, and Sahay (2021), using cross-country evidence, suggest that digital financial inclusion can unlock economic growth, but its distributional outcomes are highly dependent on regulatory quality and institutional frameworks.Similarly, Magwedere and Marozva (2025) show that the relationship between financial technology development and income inequality is nonlinear and context-dependent, shaped by financial system maturity and technological diffusion. These international findings reinforce the view that the effects of digital inclusive finance on income inequality are not uniform and depend critically on economic, institutional, and technological conditions.

This paper adopts the Chinese Digital Inclusive Finance Indicator System developed by Feng et al. (2019) of the Center for Digital Finance at Peking University.The index system is primarily constructed based on three dimensions: coverage, usage depth, and digitalization. Coverage primarily reflects the prevalence of digital financial services, such as account penetration; usage depth primarily reflects the extent to which households and businesses utilize digital financial products, including financial services such as payments, credit, investment, and insurance; and digitalization reflects the level of convenience and efficiency of financial services supported by digital technology.

In terms of index calculation, this study first established a multi-level indicator system and standardized the data for each basic indicator to eliminate differences in units of measurement between indicators. Regarding the determination of weights, the study employed the Analytic Hierarchy Process (AHP) at the dimensional level to determine the weights for the three dimensions—

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coverage, usage depth, and digitalization—and used the coefficient of variation method within each dimension to objectively assign weights to specific indicators, thereby reflecting the information differences among them.The weights for each indicator are as follows:

Table 1: Weighting of Dimensions in the Digital Inclusive Financial System

Composite Index	Primary Dimension	Secondary Dimension
Digital Inclusive Finance Index	Coverage Breadth(54.0%)	
	Depth of Use(29.7%)	Payment Services(4.3%),Money Market Fund Operations(6.4%),Credit Business(38.3%),Insurance Business(16.0%),Investment Business(25.0%),Credit-Related Business(10.0%)
	Digitalization level(16.3%)	Creditization(9.5%),Facilitation(16.0%),Affordability(24.8%) ， Mobileization(49.7%)

Finally, by weighting and aggregating the various indicators, the study derives a digital inclusive finance index for each region, thereby comprehensively measuring the level of development of digital inclusive finance.

To better estimate the impact of digital inclusive finance on the urban–rural income gap, several control variables are introduced. Wan, Zhang, and Zhao (2022) find that urbanization plays an important role in reducing income inequality by improving labor allocation efficiency and expanding economic opportunities. Chen and Ma (2022) argue that industrial structure significantly influences income distribution by affecting employment patterns and wage levels across sectors. Mihnenoka and Senfelde (2015) show that the share of the primary industry reflects structural characteristics of regional economies and may influence income inequality because the primary sector is generally associated with lower productivity and wages. Muszynska and Wedrowska (2023) find that education level plays an important role in shaping income distribution by affecting individuals' earning capacity and labor market opportunities. Therefore, urbanization level, industrial structure, the share of the primary industry, and education level are included as control variables in this study.

III. METHODOLOGY & DATA

This study employs a panel data econometric approach to examine the impact of digital inclusive finance on the urban–rural income gap in Northwest China. The dataset covers 12 provinces from 2014 to 2023, forming a balanced panel dataset with both cross-sectional and time dimensions. Compared with cross-sectional or time-series analysis, the panel data model can effectively control for unobserved heterogeneity across regions and over time, thereby improving the reliability of the estimation results.

Following the Hausman test, this study employs a fixed-effects model to empirically analyze the impact of digital financial inclusion on the urban-rural income gap. The basic model specification is as follows:

$$Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it} + u_i + \eta_t \tag{1}$$

Here, Y_{it} represents the explained variable for the i-th individual in period t, X_{it} denotes the explanatory variable, α is the intercept term, β is the slope term, ε_{it} is the error term, i indicates the cross-sectional dimension, t denotes the temporal dimension, u_i represents the individual effect, and η_t is the period effect.

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This study uses the Theil index to measure the urban-rural income gap.The Theil Index sensitively reflects income distribution imbalances, particularly when a small number of high- or low-income groups exist. It possesses decomposability, allowing the overall gap to be split into intra-urban/rural disparities and inter- urban/rural disparities, facilitating in-depth analysis of digital inclusive finance's impact on income distribution across different regions.the calculation formula as follows:

$$\mathrm{Gap} = \mathrm{T} = \sum_{i=1}^{2} \frac{Y_{(i.t)}}{Y_t} \times \mathrm{Ln}[(\frac{Y_{(i.t)}}{Y_t} / \frac{X_{(i.t)}}{X_t})] \tag{2}$$

Where i=1 represents urban areas and i=2 represents rural areas. $Y_{(i.t)}$ denotes the disposable income in urban or rural areas in year t,Y_t denotes the total disposable income in year t; $X_{(i.t)}$ denotes the population in urban or rural areas in year t, and X_t denotes the total population in year t.

To validate the robustness of the research findings, this paper selects the Gini coefficient as an alternative measure of urban-rural income disparity alongside the Theil index.These two indicators focus on different aspects of income distribution.The Theil index emphasizes the structural differences between urban and rural areas, while the Gini coefficient reflects the overall level of income inequality.Using both measures can also help test whether the main results are robust, meaning that the core conclusion does not depend on a specific way of measuring the income gap.The formula for calculating the Gini Coefficient is as follows:

$$G = \frac{p_u p_r |y_u - y_r|}{\bar{y}} \tag{3}$$

Where p_u is the share of urban population, p_r is the share of rural population, y_u is urban per capita income, y_r is rural per capita income, and $\bar{y}$ is overall per capita income.

This study systematically examines the linear and nonlinear effects of digital inclusive finance on urban-rural income disparities within a fixed-effects panel model framework, employing a stepwise regression approach. Specifically, four models are constructed sequentially by progressively introducing control variables and nonlinear terms to assess the robustness of core explanatory variable estimates and their potential stage-specific characteristics.

$$\mathrm{Gap} = \beta_{a0} + \beta_{a1}\mathrm{DIF}_{it} + \mu_{it} + u_i + \eta_t \tag{4}$$

This model includes only the core explanatory variable, the Digital Inclusive Finance Index, to preliminarily examine whether digital inclusive finance significantly impacts the urban-rural income gap, providing a baseline reference for subsequent analysis.

$$\mathrm{Gap} = \beta_{b0} + \beta_{b1}\mathrm{lnDIF}_{it} + \beta_{b3}\mathrm{Ur}_{it} + \beta_{b4}\mathrm{IS}_{it} + \beta_{b5}\mathrm{Emp}_{it} + \beta_{b6}\mathrm{Edu}_{it} + \mu_{it} + u_i + \eta_t \tag{5}$$

Building upon Model (1),introduce control variables to account for the influence of other socioeconomic factors on the urban-rural income gap, thereby testing the robustness of the estimated coefficients for digital inclusive finance.

However, existing research suggests that the impact of digital inclusive finance on income distribution may not be monotonically linear but exhibit nonlinear characteristics (e.g., an inverted U-shaped relationship). Therefore, this study further incorporates a squared term for digital inclusive finance development into the model to explore its potential nonlinear effects:

$$\mathrm{Gap} = \beta_{c0} + \beta_{c1}\mathrm{DIF}_{it} + \beta_{c2}\mathrm{DIF}_{it}^2 + \mu_{it} + u_i + \eta_t \tag{6}$$

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By incorporating a quadratic term of the digital inclusive finance index, this model preliminarily examines whether its impact on the urban-rural income gap exhibits nonlinear characteristics, thereby providing a theoretical foundation for inflection point analysis.

$$Gap = \beta_{c0} + \beta_{c1} lnDIF_{it} + \beta_{c2} lnDIF_{it}^2 + \beta_{c3} Ur_{it} + \beta_{c4} Is_{it} + \beta_{c5} Emp_{it} + \beta_{b6} Edu_{it} + \mu_{it} + u_i \quad (7)$$

This step characterizes the nonlinear impact of digital inclusive finance on urban-rural income disparities while controlling for relevant factors. It serves as the core model for calculating inflection points and estimating their confidence intervals in this study.

Next,this study will calculate the inflection point at which digital inclusive finance impacts the urban-rural income gap based on estimated coefficients, specifically the level of digital inclusive finance development corresponding to the point where marginal effects change. The inflection point will be computed using the standard quadratic function form, expressed as:

$$X^* = -\frac{\beta_1}{2\beta_2} \quad (8)$$

Here, β_1 and β_2 represent the regression coefficients for the linear and quadratic terms of digital inclusive finance, respectively.

Given that the inflection point is a nonlinear function composed of regression coefficients, its uncertainty cannot be directly obtained through the standard error of conventional linear regression. There this study will also use the Delta method to construct a confidence interval for the inflection point, assess the uncertainty of its estimate, and test whether the inflection point lies within the sample interval.

Table 2: Variables and Measures

Variable	Measurement	Symbol	Data Source
Urban-rural income gap	Theil Index	Gap	China Statistical Yearbook
Level of Digital Inclusive Finance	Natural logarithm of the Total Index	lnDIF	
Nonlinear Term of DIF	Square of lndif	$lnDIF^2$	Calculated from lndif
Gini coefficient	Calculated based on urban and rural per capita income and population shares	gini	China Statistical Yearbook
Urbanization Level	Ratio of Urban Population to Total Population	Ur	China Statistical Yearbook

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Industrial Structure	The ratio of tertiary industry output value to secondary industry output value	Is	China Statistical Yearbook
Employment Share of the Primary Sector	The proportion of the primary industry workforce in the total workforce	Emp	China Statistical Yearbook
Education Level	Average years of schooling for the population aged 6 years and older	Edu	China Statistical Yearbook

IV. EMPIRICAL ANALYSIS

IV.I. ANALYSIS OF PANEL DATA REGRESSION RESULTS

Table 3: Total Sample Regression Results

	(1)	(2)	(3)	(4)
	gap	gap	gap	gap
lnDIF	-0.064***	0.020*	0.875***	0.742***
	(-21.447)	(1.709)	(9.896)	(8.774)
Ur		-0.570***		-0.277***
		(-7.707)		(-4.186)
Is		0.023***		0.018***
		(4.818)		(4.813)
Emp		0.026		0.040***
		(1.648)		(3.314)
Edu		0.003		0.007***
		(0.915)		(3.214)
$lnDIF^2$			-0.085***	-0.070***

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			(-10.620)	(-8.588)
_cons	0.465***	0.244***	-2.120***	-1.807***
	(27.882)	(7.727)	(-8.698)	(-7.527)
N	120	120	120	120
R2	0.811	0.897	0.909	0.940
F	459.970	179.348	526.664	267.330

*** p<0.01, ** p<0.05, * p<0.10

Table 3 reports the panel regression results on the impact of digital inclusive finance on the urban–rural income gap. Model (1) includes only the core explanatory variable, namely the level of digital inclusive finance (lnDIF). The results show that the coefficient of lndif is −0.064 and is statistically significant at the 1% level, indicating that, without controlling for other factors, the development of digital inclusive finance helps reduce the urban–rural income gap.

In Model (2), after introducing control variables such as the level of urbanization (Ur), industrial structure (Is), employment level (Emp), and education level (Edu), the coefficient of lndif turns positive (0.020) and is significant at the 10% level. This suggests that, after controlling for relevant socioeconomic factors, the direction of the impact of digital inclusive finance on the urban–rural income gap changes. This result implies that the baseline model may suffer from omitted variable bias, and that the inclusion of key control variables allows for a more accurate estimation of the effect of digital inclusive finance. Meanwhile, the coefficients of the control variables are generally consistent with expectations: Ur has a significantly negative effect, indicating that it helps narrow the income gap, while Is and Edu show positive coefficients, suggesting that they may, to some extent, widen the income gap.

To further examine the nonlinear relationship between digital inclusive finance and the urban–rural income gap, Models (3) and (4) incorporate the quadratic term of digital inclusive finance ($lnDIF^2$). The results indicate that, both with and without control variables, the coefficient of the linear term is significantly positive, while that of the quadratic term is significantly negative, confirming the existence of an inverted U-shaped relationship. This finding remains robust across different model specifications, suggesting that the nonlinear relationship is stable and reliable.

IV.II. NONLINEAR EFFECTS AND TURNING POINT ANALYSIS

Table 4: Turning Point Estimation and Confidence Interval

gap	Coefficient	Std. err	z	P>|z|	[95% conf. interval]
_nl_1	5.320865	0.0650657	81.78	0	5.193338 5.448391

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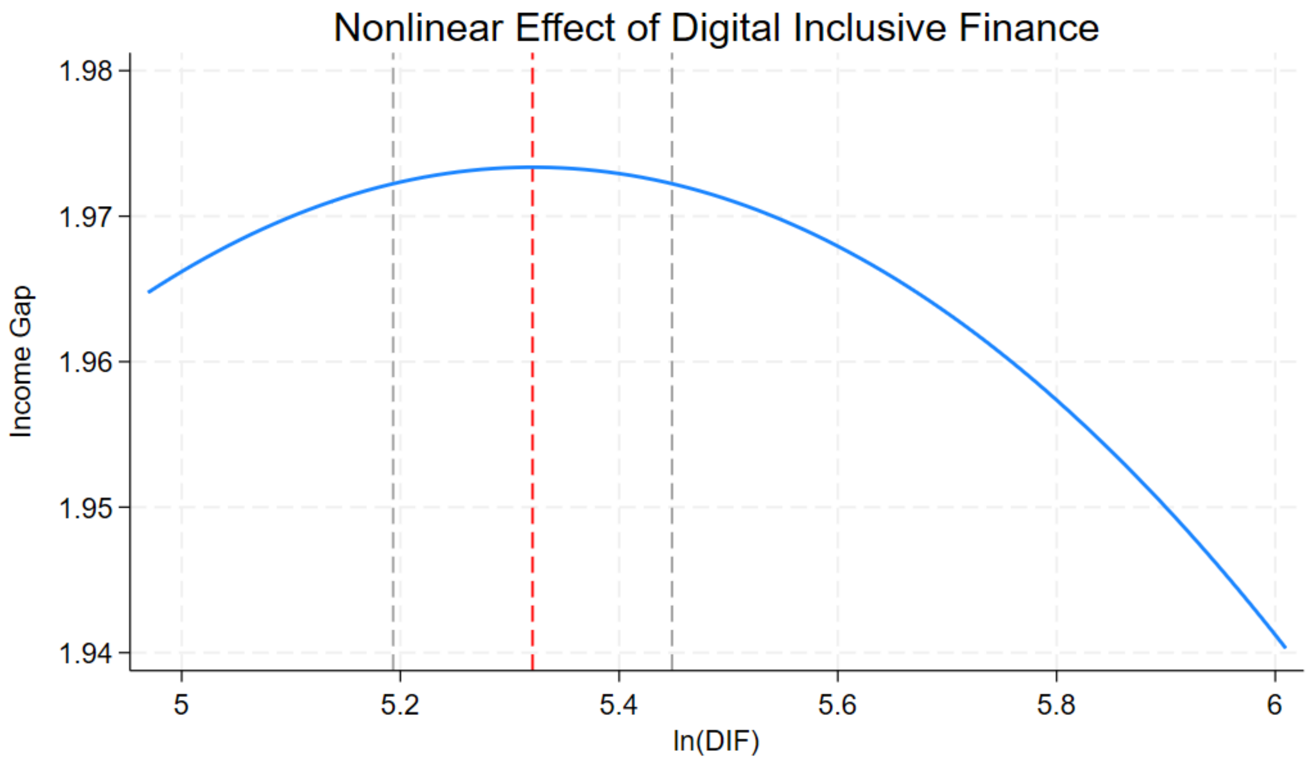

Figure 1: Nonlinear Effect and Turning Point of Digital Inclusive Finance on the Urban－Rural Income Gap

To further examine the nonlinear relationship between digital inclusive finance and the urban–rural income gap, this study incorporates the quadratic term of digital inclusive finance into the regression model and calculates the turning point based on the estimation results. The findings show that the coefficient of the linear term is significantly positive, while that of the quadratic term is significantly negative, indicating the existence of a significant inverted U-shaped relationship between the two.

On this basis, the turning point is estimated using the Delta method. The results indicate that the turning point is approximately 5.321 and is statistically significant at the 1% level, suggesting that this threshold is highly reliable. Meanwhile, the 95% confidence interval ranges from 5.193 to 5.448, and the relatively narrow interval further demonstrates the stability of the estimation.

As illustrated in Figure X, the nonlinear relationship can be more clearly observed: as the level of digital inclusive finance increases, the urban–rural income gap first rises and then declines. Specifically, before reaching the turning point, the development of digital inclusive finance may widen the income gap; however, once this threshold is exceeded, its effect reverses and begins to significantly reduce the income gap.

IV.III. ANALYSIS OF ROBUSTNESS TEST RESULTS

Table 5: Regression results for the robustness test

	(5)	(6)
	gini	gini
lnDIF	-0.078***	0.027*

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	(-21.177)	(1.867)
Ur		-0.751***
		(-8.107)
Is		0.026***
		(4.299)
Emp		0.011
		(0.561)
Edu		0.007**
		(2.080)
_cons	0.654***	0.376***
	(31.789)	(9.490)
N	120	120
R2	0.807	0.891
F	448.484	169.002

***p<0.01, **p<0.05, *p<0.10

From the regression results, in Model (5) without control variables, the coefficient of lnDIF is −0.078 and is statistically significant at the 1% level, indicating that its development helps reduce the urban‑rural income gap. In Model (6), after introducing control variables such as the Ur,Is, Emp, and Edu, the coefficient of lnDIF turns positive (0.027) and is significant at the 10% level, suggesting that the direction of its impact changes after controlling for relevant socioeconomic factors.

A further comparison with the baseline regression results using the Theil index as the dependent variable shows that, regardless of whether control variables are included, both the sign and the changing pattern of the coefficient of lnDIF remain consistent. Specifically, it exhibits a significantly negative effect in the baseline model, but turns positive after the inclusion of control variables. This indicates that the empirical findings of this study do not depend on the specific measure of income inequality.

In addition, the results for the control variables are broadly consistent with those of the baseline regression. Ur is consistently negative and statistically significant, suggesting that it helps narrow the urban‑rural income gap. In contrast, Is and Edu have positive coefficients, implying that they may, to some extent, widen the income gap, while the effect of Emp is not statistically significant.

V. CONCLUSION

This study examines the impact of digital inclusive finance on the urban‑rural income gap in Northwest China using panel data from 2014 to 2023. The findings suggest that digital inclusive finance does not exert a unidirectional effect on the income gap; rather, it exhibits a clear stage-dependent characteristic, with its impact undergoing structural changes as its level of development increases.Specifically, in the early stage of development, disparities in digital infrastructure, financial accessibility, and digital literacy may lead digital inclusive finance to widen the urban‑rural income gap to some extent. However, as its coverage expands and its depth of use increases, the inclusive nature of digital finance gradually emerges, thereby contributing to the reduction of the income gap. This indicates that the effect of digital inclusive finance on income distribution follows a dynamic pattern of "initial divergence followed by convergence."

Further analysis shows that the effectiveness of digital inclusive finance is contingent upon broader socioeconomic conditions. Its impact is closely related to factors such as urbanization, industrial structure, and human capital, suggesting that digital inclusive finance does not operate in isolation but is embedded within the regional development framework. Therefore, its role in reducing inequality relies on a solid foundation of economic and institutional development.

Based on these findings, this study suggests that policy efforts should shift from merely expanding the scale of digital inclusive finance to improving its quality. While continuing to promote its development, greater attention should be paid to narrowing the digital divide, particularly by enhancing digital infrastructure in rural areas, improving financial literacy, and strengthening institutional support. Only under an inclusive development framework can digital inclusive finance fully realize its potential in reducing the urban‑rural income gap and promoting balanced regional development.

REFERENCES

1. Yu, N., & Wang, Y. (2021). Can digital inclusive finance narrow the Chinese urban–rural income gap? The perspective of the regional urban–rural income structure. Sustainability, 13(11), 6427.
2. Gao, J., Wu, Y., & Li, H. (2024). Digital Inclusive Finance, Rural Loan Availability, and Urban–Rural Income Gap: Evidence from China. Sustainability (2071-1050), 16(22).
3. Wang, S., Wu, C., & Fu, B. (2024). The dual effects of digital inclusive finance on the urban-rural income gap: An empirical investigation in China's Yangtze River Delta region. Finance Research Letters, 69, 106049.
4. Becha, H., Kalai, M., Houidi, S., & Helali, K. (2025). Digital financial inclusion, environmental sustainability and regional economic growth in China: insights from a panel threshold model. Journal of Economic Structures, 14(1), 4.
5. Yao, L., & Ma, X. (2022). Has digital finance widened the income gap?. Plos one, 17(2), e0263915.
6. Zhang, L., Liu, J. K., Li, Z. H., Yu, J. Y., & Ding, C. J. (2024). Inclusive or Fraudulent: Digital Inclusive Finance and Urban–Rural Income Gap. Asia-Pacific Financial Markets, 1-34.
7. region. Finance Research Letters, 69, 106049.
8. Asongu, S. A. (2024). The role of mobile money innovations in poverty and inequality outcomes in sub-Saharan Africa. Information Technology & People / Journal of Economic Studies.
9. Khera, P., Ogawa, M. S., & Sahay, M. R. (2021). Is digital financial inclusion unlocking growth?. International Monetary Fund.
10. Magwedere, M. R., & Marozva, G. (2025). Financial technology and income inequality: an empirical investigation. Discover Global Society, 3(1), 1-13.
11. Feng, G., Jingyi, W., Zhiyun, C., Yongguo, L., Fang, W., & Aiyong, W. (2019). The Peking University digital financial inclusion index of China (2011-2018). Institute of Digital Finance, Peking University, April, 1-70.
12. Wan, G., Zhang, X., & Zhao, M. (2022). Urbanization can help reduce income inequality. Npj Urban Sustainability, 2(1), 1.
13. Chen, D., & Ma, Y. (2022). Effect of industrial structure on urban‑rural income inequality in China. China Agricultural Economic Review, 14(3), 547-566.

14. Muszynska, J., & Wedrowska, E. (2023). Does education affect income inequality? A comparative review of fourteen European countries. Экономика региона, 19(2), 397-409.
15. National Bureau of Statistics of China. (2024). China statistical yearbook [Annual statistical compilation]. China Statistics Press.