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The impact of new digital infrastructure on green total factor productivity

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As a new engine driving economic development, new digital infrastructure plays a significant role in enhancing green total factor productivity. Based on 2011–2020 panel data covering 30 Chinese provinces, this study empirically investigates the effects and mechanisms of new digital infrastructure on green total factor productivity. The results show that new digital infrastructure can significantly improve regional green total factor productivity, and this conclusion remains valid after a series of robustness tests and regressions of instrumental variables. Further mechanism research shows that new digital infrastructure indirectly promotes the growth of green total factor productivity by improving capital misallocation and driving technological innovation, while there is no mediating mechanism of labor misallocation. In addition, there is significant heterogeneity in the impact of new digital infrastructure on green total factor productivity. Especially during periods of high government attention, in the eastern regions, and in areas with higher levels of human capital, the positive incentive effect of new digital infrastructure is more significant. This study provides empirical evidence and policy references for promoting and amplifying the green growth effects of new digital infrastructure.

KEYWORDS

new digital infrastructure, green total factor productivity, resource misallocation, technological innovation, heterogeneity

1 Introduction

Currently, China is confronted with increasingly prominent contradictions between resources, environment, and economic development, urgently necessitating a transition from traditional extensive production modes to green production. Enhancing green total factor productivity (GTFP) is a fundamental approach to achieve a green, low-carbon transformation and high-quality development. Meanwhile, the rise of new-generation information technologies, represented by 5G networks, big data, and artificial intelligence, is becoming a new engine for the digital and low-carbon transformation of the real economy, providing significant opportunities for green development. Since the concept of new digital infrastructure was first proposed at the Central Economic Work Conference in 2018, the meetings of the Central Political Bureau and government work reports have repeatedly emphasized accelerating the construction of new digital infrastructure. In 2023, the Central Committee of the Communist Party of China and the State Council issued the "overall layout plan for the construction of digital China", which clearly set out the development goal of "connecting the main arteries of digital infrastructure and consolidating the foundation of digital China", thus guiding the direction for the medium and long-term construction and development of China's digital infrastructure. As a vital carrier in the implementation of the digital China construction strategy, can new digital infrastructure effectively enhance GTFP? What are the internal mechanisms of its impact? Clarifying these issues is of significant theoretical and practical importance in leveraging the green value of new digital infrastructure, improving resource allocation, and promoting sustainable green economic development.

Existing literature primarily focuses on the impact of traditional infrastructure such as transportation on GTFP. There are two prevailing views in academia: First, the construction of transportation infrastructure can effectively improve the spatial accessibility of production factors and products, expand their mobility range, and accelerate their speed of movement, thereby fostering technological advancement and efficiency improvements, enhancing GTFP (Aschauer, 1989; Bronzini and Piselli, 2009; Arbues et al., 2015; Holl, 2016; Tan et al., 2022). Second, investment in transportation infrastructure may crowd out government funding for environmental protection, potentially exacerbating environmental pollution, and excessive investment inevitably causes ecological damage, thus inhibiting GTFP (Shu et al., 2013; Guttikunda et al., 2014).

However, traditional transportation infrastructure and new digital infrastructure are fundamentally different. Traditional infrastructure primarily focuses on labor and capital as its main elements, whereas new digital infrastructure is centered around data and information as new types of production factors, extensively permeating various fields of economic and social development. Therefore, their mechanisms of impact on GTFP are bound to differ.

As critical infrastructure for the digital economy (Schade and Schuhmacher, 2022; Wu et al., 2023), new digital infrastructure emerges from the continuous integration, overlay, and iteration of new generation information technologies such as data centers, artificial intelligence, 5G networks, industrial Internet, and the Internet of Things. Research on new digital infrastructure mainly concentrates on its economic effects or environmental impacts. The proliferation of telecommunications infrastructure (Roller and Waverman, 2001; Datta and Agarwal, 2004; Mitra et al., 2016; Pradhan et al., 2016), the Internet (Choi and Yi, 2009; Czernich et al., 2011; Tranos, 2012; Chu, 2013; Paunov and Rollo, 2016; Harb, 2017; Lin et al., 2017), and artificial intelligence (Fernald and Jones, 2014; Graetz and Michaels, 2015; Hémous and Olsen, 2016; Aghion et al., 2017; Lu, 2021) significantly boost regional economic growth. Further studies have validated the economic effects of new digital infrastructure from the perspectives of industrial structure upgrading (Gong et al., 2023), technological innovation (Crescenzi and Gagliardi, 2018), and total factor productivity (Nakatani, 2021; Tang and Zhao, 2023). Regarding its environmental impact, scholars have found that new digital infrastructure helps reduce the energy consumption intensity of the production sector and decrease CO_2 emissions, demonstrating an environmentally friendly effect (Almulali et al., 2015; Wang and Han, 2016; Lan and Zhu, 2023; Tang and Yang, 2023). However, some studies argue that new digital infrastructure, by promoting economic growth, has expanded the scale of energy consumption and is not environmentally friendly (Zhou et al., 2019; Ren et al., 2021; Liu and Zhang, 2023).

In summary, existing literature provides valuable references for studying the impact of new digital infrastructure on GTFP but has its limitations. Most research focuses on the impact of traditional transportation infrastructure on GTFP, while studies on new digital infrastructure either concentrate on its economic effects or its environmental impacts, without integrating the two. There is a lack of a systematic exploration from the perspective of green development on the economic and environmental benefits of new digital infrastructure, and its mechanism of action on GTFP is not adequately discussed. In light of this, our study focuses on new digital infrastructure, represented by the new information technologies, as the subject of research. Utilizing panel data from 30 provincial governments in China from 2011 to 2020, we calculate the annual green total factor productivity to thoroughly investigate the impact of new digital infrastructure on this productivity. Moreover, we specifically explore the mechanisms of this impact from the perspectives of resource misallocation and technological innovation. The marginal contributions of this study are: 1) By improving the comprehensive evaluation indicators of new digital infrastructure, it examines its impact on GTFP, further expanding the research boundaries of the economic effects of new digital infrastructure. 2) Using a mediating effect model, it reveals the "black box" of the mechanism from "new digital infrastructure to GTFP" based on resource misallocation and technological innovation, providing empirical support to understand the transmission path between new digital infrastructure and GTFP. 3) It fully demonstrates the impact of internal and external factors on the relationship between new digital infrastructure and GTFP from the perspectives of government attention, regional differences, and the level of human capital development, providing evidence rooted in China's local logic to promote the green transformation of the economy.

The rest of this study is structured as follows. Section 2 deals with the theoretical foundation and research hypotheses; Section 3 covers the data and model setting; Section 4 provides the analysis of empirical results; Section 5 addresses the study of heterogeneity; and Section 6 concludes with a summary and policy recommendations.

2 Theoretical analysis and research hypotheses

The rapid development of new digital infrastructure including big data, 5G, artificial intelligence and industrial Internet, has a significant influence on GTFP. This paper constructed an theoretical framework that examines how new digital infrastructure affects GTFP from two perspectives: direct effect and indirect effect.

2.1 Direct impact of new digital infrastructure on GTFP

The direct effect of new digital infrastructure on GTFP is mainly reflected in the following two aspects:

First, the construction of new digital infrastructure increases regional capital input, directly influencing GTFP. As a vital form of fixed asset investment, new digital infrastructure brings about a multiplier effect. This effect not only multiplies the demand for related products and services beyond the increment in investment but also facilitates the rapid expansion of sectors with a higher investment-to-consumption ratio. Such expansion impacts the accumulation of regional material and human capital and is conducive to the enhancement of technological innovation and imitation capabilities, thus promoting the growth of GTFP.

Second, the development of the traditional economy struggles to detach from its heavy dependence on energy and environmental resources, rendering high-input, high-consumption, and high-pollution growth models unsustainable. Digital technologies enabled by new digital infrastructure can refine production processes, enhance precision in production management, and substantially reduce the overconsumption of tangible resources and energy in traditional industrial production. This accelerates the adjustment of the factor structure and enhances the utilization efficiency of factor (Ishida, 2015; Lan and Zhu, 2023). Additionally, new digital infrastructure can expedite the upgrading and optimization of traditional infrastructures, such as transportation, by developing intelligent transportation systems, optimizing traffic efficiency, reducing vehicle carbon emissions, and promoting high-quality green economic development through the effect of energy conservation and emission reduction. Through the comprehensive analysis conducted above, the following hypothesis is proposed.

H1. New digital infrastructure can boost GTFP.

2.2 Indirect impact of new digital infrastructure on GTFP

Currently, China's economy has entered a new normal growth stage characterized by the "triple-phase overlap". To achieve high-quality green economic development under this new normal, it is essential to optimize factor allocation and stimulate technological innovation. New digital infrastructure offers a novel pathway for improving resource misallocation and fostering technological innovation.

On one hand, new digital infrastructure is conducive to ameliorating resource misallocation and enhancing the efficiency of resource allocation. Market imperfections and information asymmetry in reality hinder the free flow and effective allocation of production factors. However, the widespread adoption of new digital infrastructure removes spatial constraints on production factors, reducing the spatial transportation costs of factor resources (Krugman, 1991), and promotes rapid and efficient connections and reconfigurations of labor, capital, technology, etc., among enterprises, industries, and regions. This helps optimize resource allocation, thereby mitigating resource misallocation (Hsieh and Peter, 2009; Elliott et al., 2020). Meanwhile, the construction of digital technologies like big data, cloud computing, and mobile internet leads to the digitization of traditional industries, providing more avenues for the allocation of production factors. Matching the total demand and supply of products and services precisely through artificial intelligence and big data reduces the distortion in resource allocation caused by information asymmetry in supply and demand, thus enhancing resource allocation efficiency. However, the development of digital infrastructure might accelerate the flow of various factors from less developed to more developed areas, creating a "siphonic effect" and leading to a "Matthew effect" of the strong getting stronger and the weak getting weaker, exacerbating the distortion in factor allocation. Further, since GTFP fundamentally represents resource allocation efficiency, the resource misallocation brought about by extensive economic growth models might deviate from Pareto optimality in environmental governance, energy utilization efficiency, and GTFP, causing an inefficient "lock-in effect". Therefore, new digital infrastructure can impact GTFP growth by either improving or exacerbating resource misallocation.

On the other hand, new digital infrastructure aids in promoting technological innovation (Tang et al., 2021). Firstly, it can weaken the boundaries of time and space (Bottazzi and Peri, 2003; Nelson et al., 2017; Ferreira et al., 2019), greatly enhancing the efficiency of information, technology, and knowledge dissemination (Damsa et al., 2021; Rodon and Eaton, 2021), and reducing the friction in the flow of innovation factors (Smit, 2017). This strengthens regional technological spillover effects, facilitating the sharing of knowledge and technology, and enabling innovators to access cutting-edge knowledge and technology, thereby improving the level of technological innovation. Secondly, the construction of new digital infrastructures, such as big data, 5G, artificial intelligence, and industrial Internet, provides enterprises with more convenient trading platforms and tools, reducing their communication and search costs for acquiring knowledge and technology (Goldfarb and Tucker, 2019), alleviating market information asymmetry (Elliott et al., 2020), and expanding their production scale. Good infrastructure, resulting in increasing returns to scale, enhances the capital return rate on corporate R&D investment, thereby increasing the enthusiasm of enterprises for R&D and innovation, continually strengthening technological innovation capabilities (Crescenzi and Gagliardi, 2018). In summary, new digital infrastructure has a positive effect on promoting technological innovation. Further, technological innovation can improve various socio-economic development indicators like industrial structure and economic efficiency (Li et al., 2021). It can enhance technological progress, transform scientific theories into practical outcomes, increase enterprises' resource utilization and production efficiency, and realize automation and intensive production. Moreover, technological innovation can transform or even eliminate high-consumption, high-pollution industries, leading to the emergence of low-energy, green industries and continuous upgrades in industrial structure, thereby improving the level of GTFP in the long term (Liu et al., 2016). Accordingly, we put forward the following hypotheses.

H2a. New digital infrastructure can influence GTFP by improving resource misallocation.

H2b. The siphonic effect brought by new digital infrastructure is not conducive to improving GTFP by exacerbating resource misallocation in backward regions.

H3. New digital infrastructure can influence GTFP by promoting technological innovation.

2.3 Different impact of new digital infrastructure on GTFP

Due to China's vast territory and significant differences in geographical location, natural resource endowment, and economic development levels among various regions, these disparities may have a different impact on the development of new digital infrastructure and its effect on GTFP.

First, in September 2015, Guizhou province initiated the construction of the first national-level big data comprehensive experimental zone. In 2016, the second batch of provinces authorized to build national-level big data comprehensive experimental zones was announced, including Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Henan, Shanghai, Chongqing, and Guangdong. These zones have become an important policy tool for promoting the development of China's digital economy. Post-implementation of these zones, China seized the opportunity of a new round of technological revolution and gradually focused on the construction of new digital infrastructure. Before 2016, government attention to new digital infrastructure was relatively low, with only a few regions pioneering related constructions, leading to a weaker impact on GTFP. After 2016, as government attention increased, the construction of new digital infrastructure accelerated, and its effect on enhancing GTFP became more apparent.

Second, although new digital infrastructure in China has developed rapidly, the investment in such infrastructure is unevenly distributed across regions, influenced by regional economic development and government fiscal revenues and expenditures. This imbalance may lead to significant regional differences in its impact on GTFP. Compared to the central and western regions, the eastern regions have a higher level of economic development, having shifted their economic growth model from factor-driven to innovation-driven. The eastern regions invest more in new digital infrastructure, and the influx of a large number of highly skilled workers enhances the utilization efficiency of new digital infrastructure, making its positive impact on GTFP more pronounced.

Finally, new digital infrastructure embodies a high level of technology and demands higher human capital. In regions with lower levels of human capital, due to the lower knowledge and technical content mastered by the workforce, the effect of new digital infrastructure on enhancing GTFP is weaker. In contrast, in regions with higher levels of human capital, where the workforce possesses more comprehensive and rich knowledge and skills, stronger R&D and innovation capabilities, the positive impact of new digital infrastructure on GTFP may be more significant. Based on the above analysis, this paper proposes the following hypothesis.

H4. The impact of new digital infrastructure on GTFP is heterogeneous. In periods of high government attention, as well as in eastern regions and areas with higher human capital level, the positive incentive effect of new digital infrastructure is more visible.

3 Research design

3.1 Model setting

This study aims to reveal whether new digital infrastructure can enhance GTFP. Based on the theoretical analysis mentioned above, the following basic model is constructed:

$$GTFP_{it} = \alpha_0 + \alpha_1 NDI_{it} + \alpha_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

In Eq. 1, the symbols represent the following: i represents the region. t represents the year. $GTFP_{it}$ denotes green total factor productivity, the dependent variable, measuring the level of GTFP in region i for year t. NDI denotes the new digital infrastructure, the core explanatory variable. X represents control variables, including other factors that may affect GTFP, such as economic, social, and environmental related variables. α_0 is a constant term, representing the intercept of the model. α_1 is the regression coefficient for new digital infrastructure, representing the marginal contribution of new digital infrastructure to GTFP. It indicates how GTFP changes on average with each additional unit of new digital infrastructure. u_i denotes the area fixed effect, ν_t denotes the time fixed effect, and ε_{it} is the random disturbance term.

Eq. 1 reflects the direct effect of new digital infrastructure on GTFP. To further discuss the possible transmission mechanisms of new digital infrastructure on GTFP, this study, referring to Wang et al. (2022), uses a mediation effect model to discuss whether resource misallocation and technological innovation are mediating variables between new digital infrastructure and GTFP, establishing the following econometric models:

$$M_{it} = \beta_0 + \beta_1 NDI_{it} + \beta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 NDI_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

In Eq. 2 and 3, M is designed to further investigate the channels through which new digital infrastructure influences GTFP, particularly focusing on the mediating role of resource misallocation and technological innovation.

3.2 Variable selection

3.2.1 Explained variable (GTFP)

Green Total Factor Productivity (GTFP). This study chooses the GML index based on the SBM directional distance function for measurement. The advantages of this measurement method are: on the one hand, the SBM directional distance function can better solve the slackness problem of undesired outputs and input-outputs. On the other hand, compared to the M and ML indices, the GML index can consider undesired outputs and avoid problems of linear programming being unsolvable. Specific measurement indicators include: 1) Input side: comprising capital, labor, and energy inputs. 2) Output side: includes desired and undesired outputs. Desired output: measured using the actual GDP of each region. Undesired output: considering the actual situation of pollution emissions and data availability in China, this study comprehensively selects the emissions of industrial wastewater, industrial sulfur dioxide, and industrial smoke (dust) as undesired outputs. Based on the above indicators, the GTFP change index (GML), green technological efficiency change index (EC), and green technological progress change index (TC) are calculated using MaxDEA Pro.

3.2.2 Explanatory variable (NDI)

New Digital Infrastructure (NDI). Currently, it is challenging to directly obtain relevant data on new digital infrastructure, and a single indicator can only reflect one aspect, failing to measure the real level of digital infrastructure comprehensively and objectively. Therefore, referring to the results of existing research (Ndubuisi et al., 2021), this study constructs an index system of new digital infrastructure from four dimensions and calculates the development level of new digital infrastructure in each province of China from 2011 to 2020 using the entropy weighting method. The specific measurement index system is as shown in Table 1.

TABLE 1 New digital infrastructure indicator system.

	Description of indicators	Units
New digital infrastructure	Length of long-distance optical cable	kilometers
	Mobile phone exchange capacity	Ten thousand households
	Per capita number of Internet broadband users	Ten thousand households
	Industrial robots	Number of stations

TABLE 2 Variables statistics.

Variable name and symbol	Mean	Std.D	Min	Max
Green Total Factor Productivity (GTFP)	1.8362	0.8620	0.8425	7.8259
Green Technological Efficiency(EC)	1.0152	0.2341	0.1901	2.1179
Green Technological Progress(TC)	1.7938	0.6156	1.1917	7.1497
New Digital Infrastructure (NDI)	1.3304	0.2105	1.0104	1.9620
Transportation Infrastructure (tra)	1.0501	0.5939	0.0924	2.7470
Population Density (peo)	5.4977	1.2908	2.0657	8.3640
Environmental Regulation (er)	7.6495	1.3219	2.1972	10.7175
Industrial Structure (stru)	0.4714	0.0976	0.297	0.839
Government Intervention (gov)	0.2505	0.1035	0.1103	0.6430
Labor Misallocation(τ_L)	0.3673	0.3254	0.0011	2.0771
Capital Misallocation(τ_K)	0.2830	0.2351	0.0035	1.7198
Technological Innovation (inv)	1.6721	1.1307	0.4111	6.4538
Domain Names(dn)	3.6222	1.4944	0.1074	6.7827

3.2.3 Mediating variables

Resource Misallocation (τ). This study, referring to Hsieh and peter (2009), measures the capital misallocation index τ_{Ki} and labor misallocation index τ_{Li} representing the degree of resource misallocation in a region, with formulas as follows:

$$\tau_{Ki} = \frac{1}{\gamma_{Ki}} - 1 \quad (4)$$

$$\tau_{Li} = \frac{1}{\gamma_{Li}} - 1 \quad (5)$$

In Eq. 4 and 5, γ_{Ki} and γ_{Li} are the factor price absolute distortion coefficients, representing the multiplier of resources without distortion. In practical calculations, the price relative distortion coefficient can replace it:

$$\hat{\gamma}_{Ki} = \left(\frac{K_i}{K}\right) \Big/ \left(\frac{s_i\beta_{Ki}}{\beta_K}\right) \quad (6)$$

$$\hat{\gamma}_{Li} = \left(\frac{L_i}{L}\right) \Big/ \left(\frac{s_i\beta_{Li}}{\beta_L}\right) \quad (7)$$

In Eq. 6 and 7, $s_i = \frac{p_i y_i}{Y}$ represents the output share of region i in the entire economy Y, and $\beta_K = \sum_i^N s_i\beta_{Ki}$ represents the output-weighted capital contribution value. $\frac{K_i}{K}$ is the theoretical proportion of capital used by region i. $\frac{s_i\beta_{Ki}}{\beta_K}$ is the theoretical proportion of capital that should be used by region i in the case of efficient capital allocation.

From Eq. 6 and 7, it is evident that to calculate the distortion in the allocation of capital and labor, it is necessary first to estimate the factor output elasticities of capital and labor for each region. In this context, the output variable Y_{it} is represented by the actual GDP of each province based on the year 2000; the labor input L_{it} is measured by the average annual employment number of each province; and the capital input K_{it} is represented by the fixed capital stock of each province calculated using the perpetual inventory method (Ma, 2023), with a depreciation rate of 9.6%.

Finally, this study, based on panel data from each province for the years 2011–2020, employs the Least Squares Dummy Variable method (LSDV) to estimate the factor output elasticities for each province. It then uses Eq. 4 and 5 to calculate the capital misallocation index τ_{Ki} and the labor misallocation index τ_{Li}.Given that resource misallocation can occur both due to under-allocation and over-allocation of resources, to maintain consistency in the regression direction, the study processes the resource misallocation indices by taking their absolute values. The larger the value, the more severe the resource misallocation. If the regression coefficient of the explanatory variable is negative, it indicates an improvement in resource misallocation; conversely, a positive regression coefficient suggests an exacerbation of resource misallocation.

Technological Innovation (inv): Under the backdrop of innovation-driven growth, technological progress is key to GTFP. Technological innovation brings continuous technological advancement, closely related to improvements in enterprise production efficiency, industrial structure adjustment and optimization, and intensive industrial development. Technological innovation mainly refers to enterprises' actions to improve production processes and product efficacy and enhance product competitiveness for maintaining their developmental advantages. Therefore, this study uses the number of valid patents owned by high-tech enterprises as a representation.

3.2.4 Control variables

To control for other factors influencing GTFP, this study selects the following variables for inclusion in the model, specifically:

Transportation infrastructure (tra), measured by summing the indicators of railway mileage, highway mileage, and inland waterway mileage and dividing by the administrative area of each province.

Population density (peo), measured by the number of people living per unit area of land.

Environmental regulation strength (er), represented by the investment amount in industrial pollution control.

Industrial structure upgrade (stru), represented by the proportion of the tertiary industry's added value to GDP.

Government intervention (gov), measured by the proportion of local government fiscal expenditure to GDP.

TABLE 3 Benchmark regression results.

Variables	(1) GTFP	(2) EC	(3) TC
NDI	1.169* (1.86)	0.149 (0.25)	0.818** (2.31)
tra	−0.441** (-2.57)	−0.460*** (-2.80)	−0.044 (-0.45)
peo	−0.002** (-2.34)	−0.002*** (-3.74)	0.000 (1.15)
er	0.079*** (4.37)	0.060*** (3.48)	0.031*** (3.08)
stru	−0.011 (-0.96)	−0.002 (-0.19)	−0.011* (-1.71)
gov	−1.771*** (-3.33)	−0.894 (-1.61)	0.552* (1.76)
Constant	1.787* (1.67)	1.637 (1.60)	0.628 (1.04)
Individual fixed effects	YES	YES	YES
Time fixed effects	YES	YES	YES
R-squared	0.622	0.241	0.854
N	300	300	300
F	27.944	5.387	99.178

Note: The numbers in parentheses are t-statistics; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.3 Data sources and descriptive statistics

Due to excessive missing data for Tibet, Taiwan, Macao and Hong Kong, this study focuses on 30 provinces in China from 2011 to 2020. Relevant data are sourced from the EPS database, China Statistical Yearbook, China Fixed Asset Investment Yearbook, and relevant regional statistical yearbooks. All economic indicators are deflated using corresponding price indices. Table 2 lists the descriptive statistics of each variable.

4 Empirical results and analysis

4.1 Benchmark regression test

To avoid the issue of spurious regression caused by potential non-stationarity of the data, this paper first conducts panel unit root tests on all variables. Traditional unit root test methods do not consider structural breaks and usually assume that the data generation process does not undergo structural changes. However, in the real economy, institutional transitions, changes in macroeconomic policies, financial crises, and other shocks may lead to structural breaks in the data. The presence of structural breaks often reduces the effectiveness of traditional unit root tests, leading to an excessive acceptance of the unit root hypothesis. Therefore, this paper uses panel unit root tests that allow for structural breaks to test the stationarity of the sample series. The test results show that the series of variables can reject the null hypothesis of a unit root, and it is a trend-stationary process with structural breaks (due to space constraints, the test results are included in the Appendix Table A1 of this paper).

The baseline regression model of Eq. 1 is first estimated. After the Hausman test, the hypothesis of "using random effects" is rejected, and a fixed effects model is selected for the empirical test of the impact of new digital infrastructure on GTFP. The benchmark test results are shown as the regression findings in Table 3.

Table 3 reports the estimation results of the impact of new digital infrastructure on GTFP and its decomposition. In Model (1), the estimated coefficient of new digital infrastructure is significantly positive at the 10% level, indicating that new digital infrastructure has green value and can significantly enhance GTFP, confirming Hypothesis 1 of this study. When decomposing GTFP, the dependent variables of Models (2) and (3) are green technological efficiency and green technological progress, respectively. The results show that new digital infrastructure has a positive but not significant impact on green technological efficiency, and a significant positive impact on green technological progress at the 5% level. This suggests that the effect of new digital infrastructure on enhancing GTFP is mainly reflected in green technological progress. The reason may be that the construction of new digital infrastructure is highly dependent on digital technology and related industrial development, accelerating the dissemination of information and technology, bringing about technological spillover effects to promote technological progress and achieving quality and efficiency improvements in green growth.

For control variables: 1) Transportation infrastructure negatively impacts GTFP, indicating that its construction, accompanied by increased carbon emissions in the transport sector, weakens GTFP. 2) Population density negatively affects GTFP, suggesting it inhibits GTFP. 3) Environmental regulation positively impacts GTFP, suggesting that stronger environmental regulations are conducive to enhancing GTFP. 4) The estimated coefficient of industrial structure upgrading is negative but not significant, indicating no expected positive effect on GTFP. 5) Government intervention has a negative impact on GTFP, as it prevents the market from effectively allocating resources, thereby hindering green economic growth.

TABLE 4 Results of the robustness test.

Variables	(I)	(II)	(III)	(IV)
NDI		2.683*** (3.93)	1.907* (1.74)	1.413* (1.67)
dn	0.097*** (3.75)			
L.GTFP		0.739*** (7.25)		
Control variable	Control	Control	Control	Control
Constant	−1.149*** (-3.01)		0.767 (0.42)	
Individual fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
R-squared	0.465		0.519	0.621
Sargan test		100.80***		
Underidentification test				[0.000]
Weak instrumental variable test				53.852
Overidentification test				[0.5965]
N	300	240	260	240

Note: Numbers in parentheses are t-statistics; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; numbers in square brackets are the *p*-values of the test statistics; endogeneity tests for instrumental variables use the Kleibergen-Paap rk LM, statistic, the Kleibergen-Paap rk Wald F statistic, and the Hansen J statistic to test for underidentification, weak instrumental variables, and overidentification, respectively.

4.2 Robustness test and endogeneity problem

To ensure the robustness of the results, a series of tests were conducted, including: 1) Replacing the core explanatory variable, 2) Changing the estimation method, 3) Excluding samples from municipalities. The results of these tests (Table 4) are consistent with those in Table 3, suggesting that the empirical results are robust and reliable.

However, the above analysis only used OLS regression. If there are potential endogeneity issues in the model, the estimation results might be inaccurate. This study addresses endogeneity concerns by using a two-stage least squares (2SLS) estimation with the lagged values of new digital infrastructure as instrumental variables (IV). The results, as shown in Table 4 column (IV), show no significant change in conclusions, indicating that the baseline regression results are not affected by endogeneity issues. Table 4 presents the results of robustness tests.

4.3 Mechanism analysis

Based on the theoretical mechanism analysis previously discussed, this study attempts to examine the potential channels through which new digital infrastructure impacts GTFP from the perspectives of resource misallocation and technological innovation. The specific test results are shown in Models (4) to (8) in Table 5.

In terms of labor misallocation, results from Model (4) in Table 5 indicate that the impact coefficient of new digital infrastructure on labor misallocation is positive but not significant. This suggests that the widespread application of new digital infrastructure creates high-skill positions that require workers to possess higher human capital and digital literacy. However, the enhancement of human capital in reality is a relatively long process and lags behind the pace of concurrent technological changes. This lag leads to a mismatch between workers' skills and technology-intensive positions, slowing the adjustment speed of labor supply (Acemoglu and Restrepo, 2018), and may exacerbate labor misallocation. Regarding capital misallocation, results from Model (5) show that the impact coefficient of new digital infrastructure on capital misallocation is significantly negative. This means that the construction of new digital infrastructure has improved the development level of digital finance, facilitated the expansion of digital investment and financing channels, and reduced the cost of financial transactions, thereby accelerating the flow of capital factors and ultimately enhancing regional capital allocation efficiency.

Model (6) includes both new digital infrastructure and labor and capital misallocation for empirical regression. The regression coefficient of new digital infrastructure is 0.863, significant at the 5% level, slightly lower than the coefficient of 1.169 in Model (1). The insignificant coefficient of labor misallocation indicates that the mediating effect does not hold. That is, new digital infrastructure does not alleviate labor misallocation, and thus labor misallocation does not become a mechanism through which digital infrastructure enhances GTFP. The significantly negative coefficient for capital misallocation confirms the existence of this mediating effect, validating Hypothesis 2a. That is, new digital infrastructure can alleviate capital misallocation and thus enhance GTFP.

When considering technological innovation as a mediating variable, results from Model (7) indicate that the impact coefficient of new digital infrastructure on technological innovation is significantly positive, suggesting that new digital infrastructure promotes technological innovation to some extent. Model (8), which includes both new digital infrastructure and technological innovation in the regression, finds that the regression coefficient for new digital infrastructure is 0.650.

TABLE 5 The impact mechanism of new digital infrastructure on GTFP.

Variables	Labor misallocation and capital misallocation			Technological innovation	
	(4) τ_L	(5) τ_K	(6) GTFP	(7) inv	(8) GTFP
NDI	0.277 (1.65)	−0.514*** (-4.68)	0.863** (2.03)	0.570* (1.78)	0.650 (1.51)
τ_L			−0.013 (-0.09)		
τ_K			−0.488*** (-2.96)		
inv					0.140* (1.68)
Control variable	Control	Control	Control	Control	Control
Constant	1.221***(4.25)	−0.483*** (-2.10)	0.812 (1.09)	−1.240** (-2.27)	0.400 (0.54)
Individual fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
R-squared	0.344	0.396	0.635	0.671	0.625
F	8.900	11.145	25.869	34.713	26.490
N	300	300	300	300	300

Note: Numbers in parentheses are t-statistics; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

This is a significant decrease compared to the coefficient of 1.169 in Model (1) and is no longer statistically significant; however, the regression coefficient for technological innovation is significant at the 10% level. This finding indicates that new digital infrastructure can facilitate technological innovation, thereby enhancing GTFP, confirming Hypothesis 3 presented earlier in the study. New digital infrastructure, evolving from new-generation information technology or digital technology, provides an infrastructure system that supports digital transformation, intelligent upgrades, and integrated innovation. The technological progress brought about by the layout and improvement of such infrastructure can alleviate current economic and environmental conflicts, improve energy utilization efficiency, and accelerate the upgrading of industrial structures, thereby enhancing GTFP.

The analysis of mediating effects concludes that new digital infrastructure enhances GTFP by improving capital misallocation and promoting technological innovation. Capital misallocation plays a partial mediating role in the impact of new digital infrastructure on GTFP, while technological innovation has a complete mediating effect.

5 Further heterogeneity study

5.1 Heterogeneity in government attention level

The paper previously discussed the impact of new digital infrastructure on GTFP in the baseline regression results. It then raises the question of whether the effectiveness of new digital infrastructure on GTFP is influenced by the period or the level of government attention. To address this, the study uses 2016 as a time point to divide the sample into two periods: a period of low government attention (2011–2015) and a period of high government attention (2016–2020). It examines the differences in impact across these periods with varying levels of government attention. The results, shown in column (1) of Table 6, indicate that before 2016, the impact of new digital infrastructure on GTFP was not significant. However, after 2016, the estimated coefficient of new digital infrastructure is 2.429, significant at the 1% level, suggesting that in the high-attention period, new digital infrastructure significantly promotes regional GTFP. This implies that increasing government attention to the construction of new digital infrastructure helps enhance regional GTFP.

5.2 Regional heterogeneity

Considering the differences in resource endowment, infrastructure, and economic development among regions, this study divides the sample into eastern and central-western regions to examine the impact of new digital infrastructure on GTFP. The estimation results, as shown in column (2) of Table 6, indicate that in the eastern regions, the regression coefficient of new digital infrastructure is 2.527, significant at the 5% level. However, in the central-western regions, the coefficient of new digital infrastructure is not significant. This suggests that new digital infrastructure effectively promotes the growth of GTFP in the eastern regions, while its impact is not evident in the central-western regions.

The reason for this result may be that the green promotion effect of new digital infrastructure depends on a higher level of economic development or is constrained by external conditions such as the digital environment. The eastern regions, with its superior economic environment, well-developed infrastructure, and advancements in science, education, and cultural industries, have improved the utilization efficiency of new digital infrastructure. Consequently, its contribution to enhancing GTFP is more pronounced. In contrast, the central and western regions, characterized by weaker infrastructure, lower levels of economic development, and limited innovation capacity, lack high-tech industries and high-quality human capital. Here, the construction of new digital

TABLE 6 The estimation results of heterogeneity.

Variable	(1) Government attention level		(2) Regional differences		(3) Human capital level	
	–2015	2016-	Eastern regions	Central-western regions	High	Low
NDI	− 0.015	2.429*** (2.86)	2.527** (2.18)	0.202 (0.38)	2.033** (2.49)	0.075 (0.22)
Control variable	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
F	8.553	11.388	15.671	22.826	13.291	42.566
R-squared	0.437	0.509	0.737	0.687	0.684	0.832
N	150	150	110	190	130	170

infrastructure is in a stage of high investment but low output, unable to meet the demands for technological innovation, and thus has a less significant effect on enhancing GTFP.

5.3 Heterogeneity in human capital level

Existing research has confirmed that human capital is a key factor influencing technological innovation and a core resource on which economic development relies. Variations in human capital levels may lead to heterogeneity in the impact of new digital infrastructure on GTFP. Therefore, based on the median level of average years of education in each region, the study categorizes the top 15 provinces as areas with higher human capital levels and the latter 15 provinces as regions with average human capital levels. It then examines the impact of new digital infrastructure on GTFP in these areas with different levels of human capital. The results, as shown in column (3) of Table 6, indicate that in regions with higher human capital levels, the coefficient of new digital infrastructure is significant at the 5% level, at 2.033, while in regions with average human capital levels, the coefficient is not statistically significant. This implies that regions with higher human capital levels, which are likely to have a better environment for innovation and development capabilities, can more effectively leverage new digital infrastructure to enhance GTFP. In contrast, the impact of new digital infrastructure is not significant in regions with average levels of human capital, suggesting that the presence of high human capital is instrumental in maximizing the benefits of new digital infrastructure for green economic growth.

6 Conclusion and policy recommendations

6.1 Conclusion

In the era of the digital economy, effectively integrating new digital infrastructure with the real economy is crucial for reshaping economic patterns and enhancing GTFP. This paper, based on provincial panel data from China for the years 2011–2020, explores the impact mechanism of new digital infrastructure on GTFP from the perspectives of resource misallocation and technological innovation. The conclusions are as follows: 1) New digital infrastructure can significantly enhance GTFP, primarily reflected in green technological progress. 2) The study finds that new digital infrastructure mainly enhances GTFP by improving capital misallocation and promoting technological innovation, though the mechanism of improving labor misallocation is not significant. 3) There is evident heterogeneity in the effectiveness of new digital infrastructure on GTFP. Particularly, during periods of high government attention, in eastern regions, and in areas with higher levels of human capital, the positive incentive effect of new digital infrastructure is more pronounced.

6.2 Policy implications

Accelerate the construction of new digital infrastructure to provide technical support for promoting green, high-quality economic development. During the transition period of China's economic growth, it is crucial to further unleash the technological dividends brought by the development of new digital infrastructure. Each region should combine its actual conditions with industrial and livelihood needs, and progressively focus on the cross-integration and technological diffusion of digital infrastructure. This approach will foster new business formats, models, and industries, forming new economic growth points. At the same time, innovate in the construction methods and investment and financing channels for new digital infrastructure. On one hand, considering the high technological content and long investment cycles of new digital infrastructure, market entities should be encouraged to participate and co-build according to market rules. On the other hand, local governments should increase policy support, offer tax reductions, and provide subsidies to promote the advancement of new-generation information technologies. They should expand the application scale and scenarios of new digital infrastructure to fully stimulate its role in enabling green growth.

Explore multi-dimensional pathways for new digital infrastructure to enhance GTFP. First, further optimize government guidance and support for technological innovation, increase financial inputs in science and technology, and formulate a series of tax incentives. Break down institutional barriers that hinder technological innovation and transformation, and focus on the transformation and absorption of scientific and technological achievements. Concurrently, elevate the level of human capital and strengthen the training of innovative talents. Using new digital infrastructure as a key driver, promote the shared construction and sharing of innovation platforms, optimize the environment for technological innovation, reduce the risks and costs of R&D innovation, and comprehensively enhance regional innovation capabilities. Second, strengthen the resource optimization allocation function of new digital infrastructure. Through the construction of new digital infrastructure, eliminate the barriers to the flow of production factors and accelerate the free flow of resource elements nationwide. Allocate resources to more efficient regions to create favorable conditions for new digital infrastructure to enhance GTFP.

Tailor strategies to local conditions and scientifically guide the development of new digital infrastructure in different regions. Given the heterogeneity of the impact of new digital infrastructure on GTFP, local governments should enhance the flexibility and inclusiveness of implementing the digital China construction strategy, avoiding blind imitation or replication of other regions' development models. For the central and western regions, further strengthen infrastructure construction in information transmission, scientific research, and other fields. Actively absorb technological spillovers from the eastern regions while minimizing the loss of elements, providing the necessary human capital and innovation environment for innovation-driven development. In regions with lower human capital levels, improve the labor education and training system, strengthen basic and professional training, increase the proportion of new digital talents, and promote deep coupling between digital infrastructure and human capital to empower green development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

QW: Conceptualization, Writing–original draft, Writing–review and editing, Formal Analysis. GL: Methodology, Writing–original draft, Writing–review and editing. MD: Formal Analysis, Methodology, Writing–original draft, Writing–review and editing. XZ: Conceptualization, Investigation, Methodology, Writing–original draft, Writing–review and editing. JL: Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Results for the unit root tests of panel data.

Variable name	Test form	Z(t) statistic	Critical value (5%)	*p*-value	Test conclusion
GTFP	Structural change of the intercept term	−9.6536***	−3.0732	0.0000	stationary
NDI	Structural change of the intercept term	−4.3760***	1.6700	0.0000	stationary
tra	Structural change of the intercept term	−6.9176***	1.6401	0.0000	stationary
peo	Structural change of the intercept term	−2.9078***	0.2345	0.0000	stationary
er	Structural change of the intercept term	−6.2461***	−0.0454	0.0000	stationary
stru	Structural change of the intercept term	−9.1572***	7.6556	0.0000	stationary
gov	Structural change of the intercept term	−3.7029***	−2.0673	0.0000	stationary

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