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Research article

The impact of new digital infrastructure on total factor productivity in the education service industry: evidence from China

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Abstract: The new digital infrastructure (NDI), including cloud computing and big data, has emerged as a key driver for promoting high-quality development in the education service sector. This study first constructed a dynamic measurement model for total factor productivity (TFP) in the education service sector by employing data envelopment analysis (DEA) combined with the Malmquist index method. Subsequently, based on externality theory and endogenous growth theory, a panel regression model and a mediation effect model were applied to systematically examine the direct and indirect mechanisms through which China's NDI development influences education TFP. Furthermore, a spatial Durbin model was utilized to capture the spatial spillover effects of NDI development on education TFP. The key findings are as follows: While NDI significantly enhances China's education TFP, regional disparities persist due to variations in economic foundations and technological systems, leading to differentiated benefit effects across regions. Among the components of NDI, integrated infrastructure and innovation infrastructure exert the most pronounced positive impact on TFP compared to information infrastructure. Human capital and technological progress play partial mediating roles, while spatial spillovers from neighboring regions exhibit a positive effect on education TFP. These findings underscore the transformative potential of NDI in the education sector and highlight the necessity of formulating region-specific policies and optimizing infrastructure deployment to mitigate regional disparities and maximize productivity growth. This study provides empirical evidence for leveraging strategically deployed NDI to foster educational equity and high-quality development in the digital era.

Keywords: new digital infrastructure; total factor productivity; education service industry; Malmquist index; spatial effect

JEL Codes: I20, O33, R11

1. Introduction

Germany's "Industry 4.0" strategy initiated the fourth industrial revolution, centered on AI, the industrial internet, and other technologies, by establishing cyber-physical systems to transform manufacturing into fully automated and personalized production (Mao et al., 2023; Hao et al., 2023). Unlike traditional infrastructure, new infrastructure is centered on the digitization of information technology and is the cornerstone of digital economic development (Ji et al., 2023). Conceptually, digital infrastructure encompasses the foundational facilities that support the operation of the digital economy, including conventional communication networks and data centers. As an advanced iteration of digital infrastructure, new digital infrastructure prioritizes the deployment of intelligent systems, including 5G, artificial intelligence, the industrial internet, and computing networks. Emphasizing technological innovation and industrial integration, new digital infrastructure drives structural leaps in total factor productivity through reconfiguring factor allocation mechanisms. The global new digital infrastructure is accelerating, with 7.939 billion broadband connections and a cumulative telecom investment of $2.94 trillion in 2023 (Li et al., 2024), reflecting the deep mutual promotion between new digital infrastructure and the digital economy. International experiences, such as the Silicon Valley arithmetic network in the United States and India's digital infrastructure (Makkar et al., 2023), confirm the strategic value of new digital infrastructure as the foundation of the digital economy. It is not only infrastructure in the physical sense but also a "digital foundation" that reshapes the industrial landscape and drives economic growth, playing a key role in optimizing the economic structure and promoting industrial upgrading.

As the core carrier supporting the development of the digital economy, new digital infrastructure has received widespread attention in recent years. Domestic and foreign scholars have conducted multidimensional research on its connotation, measurement, and impact. In terms of a definition, scholars generally believe that new digital infrastructure is an infrastructure system centered on new-generation information technologies such as 5G, artificial intelligence, and the industrial internet (Shang, 2020; Chao and Xue, 2022; Yu and Xu, 2023). This consensus has laid the theoretical foundation for subsequent research, but existing studies have obvious limitations in their application areas. Current research primarily focuses on economic benefits, labor employment, and technological innovation, with insufficient exploration of the impact mechanisms on the education services sector, a critical area. For example, Liu and Su (2021) examined multiple dimensions such as industrial integration, diversified financing channels, and the multiplier effect of investment, pointing out that new infrastructure can promote the digital transformation of traditional infrastructure, facilitate the transition from old to new growth drivers, and inject new vitality into the high-quality development of the Chinese economy. Bai (2017) verified the promotional effect of information network optimization on regional employment based on US broadband network data. Zhao (2022) studied the technological innovation effects of digital infrastructure but neglected the vital application scenario of education.

Total factor productivity serves as a core indicator for measuring the quality of economic growth, and its estimation methods have become well-established, including the Solow residual method, stochastic frontier analysis, and data envelopment analysis. Existing research has primarily focused on the impact of factors such as technological innovation and industrial structure on the TFP. In terms of technological innovation, Delpachitra and Van (2012) confirmed the positive driving effect of technological efficiency on productivity growth. Li and Li (2022) deconstructed the evolution mechanism of the TFP using a technology bias model, exploring the sources and mechanisms of China's TFP evolution from a new perspective of multiple effect decomposition. In the field of industrial structure, research conclusions diverge between the "structural dividend" and the "structural disadvantage". On the one hand, Zhang et al. (2009) found that sustained structural reforms in the industrial sector, leading to factor mobility and restructuring within industries, can significantly enhance industrial TFP levels and economic performance. On the other hand, Kruger (2008) and Liu and Ling (2020) pointed out that a rapid shift toward a service-sector-dominated economy or structural transformation may suppress TFP growth.

Existing research on new digital infrastructure and total factor productivity has primarily focused on the macroeconomic domain. For instance, Li et al. (2017) showed that improving production technology and transforming industrial structure in the service industry sector can significantly enhance the total factor productivity of the service industry; Chen and Zhang (2022) observed a declining contribution of traditional economic capital to growth alongside rising digital capital significance. Makkar et al. (2023) found that India's digital infrastructure drives economic growth, while Hao et al. (2023) examined digital finance's impact on banking efficiency. Nevertheless, most of these studies are based on the macro level and have not yet incorporated the education service industry into their analytical framework, lacking a systematic argument for the micro path of new digital infrastructure.

Although existing literature has revealed the heterogeneous characteristics of total factor productivity in the education industry from multiple dimensions, the theoretical relationship between new digital infrastructure and education TFP has not yet been fully established. On the one hand, research has confirmed the critical driving role of higher education in enhancing TFP: Vandenbussche et al. (2006) found that among 19 Organization for Economic Co-operation and Development (OECD) countries, only highly skilled labor (with a higher education background) significantly promoted TFP growth. Hua (2005) further demonstrated through a productivity decomposition model that university education has a significant positive impact on both technological progress and efficiency improvements, while primary and secondary education had no significant effect. Lv and Kan (2016) found that the marginal impact of expanding higher vocational education on TFP was higher than that of general higher education. On the other hand, research on industry and regional differences has also yielded fruitful results: Li et al. (2017) confirmed that improvements in service sector production technology and industrial structure transformation can enhance TFP. Zhang (2019) used a game-based cross-efficiency model to reveal that inter-provincial educational efficiency in China follows a V-shaped trend and exhibits significant regional differentiation. However, although existing research has systematically covered the heterogeneity analysis of education levels, industry fields, and regional dimensions, this traditional analytical paradigm makes it difficult to explain the changes in educational productivity in the digital economy era. The linkage mechanism between new digital infrastructure and educational TFP is still a blind spot in research, and few scholars have systematically examined the enabling effect of digital infrastructure on educational productivity.

Based on the above literature, this study aims to deconstruct the interactive mechanism between new digital infrastructure and the improvement of total factor productivity in the education service industry. It combines theoretical and empirical analysis to deeply analyze the intrinsic connection and dynamic relationship between the two, with a view to gaining a more comprehensive understanding of the far-reaching impact of new digital infrastructure on the education service industry and providing a strong basis for relevant policy-making.

This study utilizes provincial-level panel data from 30 Chinese mainland provinces (excluding Hong Kong, Macau, Taiwan, and Tibet) spanning the period between 2004–2022 to measure total factor productivity (TFP) in the education service sector using the DEA-Malmquist index approach. Through theoretical mechanism analysis and econometric model testing, the research identifies both the direct effects and transmission mechanisms through which new digital infrastructure (NDI) influences TFP in China's education service sector. It also examines its regional heterogeneity characteristics and spatial effects. The study establishes an analytical framework of "New Digital Infrastructure—TFP in the Education Service Sector", leveraging the inherent advantages of information infrastructure, innovation infrastructure, and integrated infrastructure in information dissemination and factor mobility. By comprehensively considering both human capital accumulation and technological progress, the research investigates the impact of new digital infrastructure on TFP in China's education service sector. This work provides a novel research perspective for empirically measuring the socioeconomic effects of emerging digital infrastructure, aiming to offer theoretical insights and practical references for advancing educational digitalization.

The contributions of this paper are mainly reflected in three dimensions: theoretical expansion, methodological innovation, and practical guidance.

1. At the theoretical level, existing research has predominantly focused on the shortcomings of new digital infrastructure in areas such as economic growth, employment, and green transition (Luo et al., 2022; Wang et al., 2023; Zhang, 2024). This study pioneers an analytical framework linking new digital infrastructure to total factor productivity in the education service industry, systematically demonstrating how NDI enhances TFP through dual pathways—accelerating human capital accumulation and technological advancement. This approach offers a novel perspective for understanding the development logic of education services in the digital economy era.
2. Methodologically, this study innovatively introduces a spatial dimension to quantify the spatial spillover effects of new digital infrastructure. Empirical results reveal a significantly higher indirect effect coefficient (5.811) compared to the direct effect (1.663), overcoming traditional research limitations that neglected regional synergies. This finding breaks through the limitations of conventional research that ignores regional coordination and accurately depicts the network externalities of cross-regional radiation of digital educational resources, establishing novel empirical foundations for regional coordinated development policies.
3. At the practical level, heterogeneity analysis in this study informs differentiated policy recommendations for educational digital transformation: Eastern regions should prioritize frontier applications of innovation infrastructure, while Central and Western areas ought to focus on deploying foundational information infrastructure to bridge the digital divide. In addition, the validated mediation mechanisms indicate that it is necessary to simultaneously strengthen the digital literacy training of education practitioners and build industry-university-research collaborative innovation platforms to accelerate educational technology transfer. These findings have direct practical guidance significance for optimizing the allocation of regional educational resources and promoting the high-quality development of educational services.

The subsequent sections of this paper are organized as follows: Section 2 introduces the research hypotheses. Section 3 contains the model, variables, and data. Section 4 presents baseline regression results. Section 5 conducts mechanism analysis. Section 6 performs heterogeneity analysis. Section 7 verifies the spatial spillover effect. Section 8 contains the conclusions and discussions.

2. Research hypothesis

2.1. New digital infrastructure and the high-quality development of education in China

Under the wave of digital transformation, the "Internet+" education model is reshaping the education ecology, driving structural changes in the education paradigm, teaching form, and governance system through the deep coupling of digital technology and the education system. This has attracted an increasing number of scholars to study the integration and development of the education service industry and the internet. Scholars Jung and Rha (2000) conducted a case study on the effectiveness of online education based on a cost-benefit perspective. They found that online education can effectively affect the allocation efficiency of educational resources. On the other hand, Yang (2019) researched the current situation and problems of applying virtual reality (VR) and augmented reality (AR) in education, pointing out that the integration and development of digital technology and education is an irreversible and inevitable trend.

The above research verifies the inevitability and importance of integrating and developing internet digital technology and education. Centering on the resource allocation efficiency and development difficulties of the education service industry itself, Halil Dundar and Darrall R. Lewis (1998) believe that the efficiency of the university sector plays a key role in improving the total factor productivity of higher education. In other words, improving resource allocation efficiency in the educational services sector depends on technological progress and follows the intrinsic law of total factor productivity. As for the factors affecting total factor productivity in the education service industry, Yang and Xiao (2023), with the background of high-quality development of education in the digital era, found that the improvement of total factor productivity in China's education service industry needs to rely on technological progress and the digital transformation of education. Starting from the trinity of education, science, technology, and talent, Sun and Zhu (2024) found that the new education infrastructure has played a significant positive role in promoting the development of China's education support system.

This paper's core concern is the impact of new digital infrastructure on the total factor productivity of the education service industry. The integration and development of the education service industry with new infrastructure has contributed to the gradual blurring of the boundaries of the industry, making the education service industry present itself to consumers in the form of a brand new business format. On the one hand, the new digital information infrastructure can not only deeply integrate with various elements within the education service industry but also connect the education service industry with other industries to form a new industrial ecosystem; on the other hand, through the use of new technologies, tools, and modes, the education service industry can realize innovations in terms of service content, service mode, and service targets, and better satisfy diversified and personalized needs of consumers. Through the use of new technologies, tools, and models, the education service industry can achieve innovation in service content, service mode, and service targets to better meet consumers' diversified and personalized needs. What is particularly crucial is that this new industry pattern is the key to tapping the development potential of the education service industry and realizing the high-quality development of the industry.

Overall, in the era of the digital economy, the rapid development of new digital infrastructure has injected strong vitality into the education service industry, greatly releasing its development potential. As a result, the education service industry can respond to market demand more efficiently, achieve a higher supply and demand balance level, and thus promote total factor productivity growth. Based on this, this paper proposes research hypothesis 1:

Hypothesis 1: New digital infrastructure can enhance total factor productivity (TFP) in the education service industry.

2.2. The mediating role of human capital

Under the endogenous growth theory framework, scholars have demonstrated profound driving mechanisms of knowledge elements and human capital on economic growth across multiple dimensions. Romer (1986) was the first to establish the central role of knowledge accumulation. His research showed that the accumulation of specialized knowledge could significantly increase the marginal returns of capital and labor through a dual mechanism of direct increasing returns and indirect spillover effects. The non-competitive and partially exclusive nature of knowledge provides a theoretical basis for sustained economic growth. Lucas (1988) further constructed a human capital-driven model, demonstrating that human capital accumulation not only counteracts diminishing returns to physical capital but also stimulates technological dynamism by enhancing individual innovative capacity, thereby constituting an endogenous growth engine.

The Nelson-Phelps model deepens this theoretical framework from the perspective of transmission mechanisms, explicitly proposing that human capital does not directly influence economic growth but rather exerts a broad impact through total factor productivity, a core intermediate variable (Nelson and Phelps,1966). The central mechanism of this effect is the diffusion of technology, the essence of which is the formation and accumulation of human capital. Total factor productivity consists of two core elements, namely, technological progress and technological efficiency, both of which human capital plays a crucial role but has a powerful impact on the former. The innovative capacity embedded in human capital and its ability to absorb and apply advanced technology from abroad can directly affect technological progress, which in turn promotes the improvement of total factor productivity. Technological progress and innovation are rooted in human intelligence and creativity. Therefore, there is no way to talk about scientific and technological progress without sufficient human capital. When the stock of human capital can be increased, and the quality can be improved, the scope of technology diffusion will continue to expand. The diffusion speed will continue to accelerate, and human capital will also drive the total factor productivity by promoting technological progress.

The introduction and implementation of new digital infrastructure policies will change the structure of labor demand and supply. The popularization of new digital infrastructure has promoted the reform of education informatization. Breakthroughs in digital technology have broken the constraints of time and space, making it more convenient to access educational resources, which is conducive to the improvement of knowledge and skill levels and the accumulation of innovative human capital. At the same time, the new business models and modes of operation brought about by the digital economy have forced workers to learn new technologies and concepts, improve their innovation capabilities, and adapt to the updated skill requirements of their jobs. Jiao et al. (2023) found that urban digital infrastructure attracts the inflow of highly skilled entrepreneurial talent, and the formation, accumulation, and application of digital entrepreneurial resources it activates serve as essential transmission channels. McCoy et al. (2018) also found that regions with higher broadband coverage rates exhibit more frequent entrepreneurial activities and attract more businesses to establish operations there.

Numerous studies have shown that the accumulation of human capital primarily drives the high-quality development of the education service industry through quantitative accumulation and vertical quality improvement. Higher education human capital plays a more prominent role in promoting cutting-edge innovation in education technology, while vocational education human capital enhances the adaptability of technology applications (He et al., 2013). High-tech talent accelerates the process of catching up with technological frontiers by enhancing independent innovation capabilities, thereby improving total factor productivity (Ma, 2019). Zhang's (2022) research results demonstrate the key role of higher education in enhancing total factor productivity, highlighting that the expansion of scale and quality improvement of higher education are not only directly associated with technical efficiency changes but also accelerate technical efficiency improvement and technological progress by increasing the stock of human capital. Additionally, the study by Chen Zhao et al. (2004) shows regional differences in the impact of education on total factor productivity, indicating that the role of human capital varies across different regions.

As automation and intelligent technologies are increasingly applied in the education services sector, only those with higher-quality innovative human capital can meet the demands of the education industry chain upgrade for composite skills, digital management capabilities, and interdisciplinary knowledge integration abilities. The accumulation of such innovative human capital not only helps cultivate the competitive advantages of new education-related industries but also significantly enhances the risk-resilience and recovery capabilities of the education industry chain. Additionally, compared to conventional human capital, innovative human capital demonstrates higher labor productivity and production contribution rates in areas such as education service innovation and educational technology research and development. Optimizing the efficiency of educational resource allocation and driving innovations in education service models significantly reinforces the developmental advantages of regional education industries. Therefore, accelerating the construction of new digital infrastructure, promoting the deep integration of digital technology and the education service industry, and thereby promoting the accumulation and optimal allocation of human capital are effective ways to improve the total factor productivity of the education service industry. Based on the above analysis, this paper proposes the following research hypothesis:

Hypothesis 2: The new digital infrastructure enhances the TFP of China's education service industry by increasing human capital.

2.3. The mediating role of technological progress

Based on relevant literature, it can be argued that new digital infrastructure promotes technological progress in the education service industry through four aspects: promoting research and development innovation, process optimization, service upgrades, and resource allocation optimization.

In terms of R&D innovation, both the comparative advantage theory and the technology catch-up theory argue that R&D innovation is one of the pathways for corporate transformation and upgrading (Costinot, 2009), and this logic also applies to the education service sector. On the one hand, the convergence and application of new digital infrastructure will increase the demand for technological resources in the education service industry, and the continuous accumulation of R&D resources will further release the innovation potential of the education service field and promote technological innovation. On the other hand, the convergence and application of new-generation information technology will motivate the education service industry to give full play to its unique comparative advantages, promote technological collaboration and resource sharing, and improve the utilization efficiency of innovation factors (Hou Shiyin et al., 2021). Under the impetus of these positive factors, a series of innovative achievements have emerged, significantly enhancing the R&D innovation capabilities of the education service sector and optimizing its service quality and efficiency.

At the process optimization level, the widespread application and continuous deepening of digital technologies provide a more scientific basis for planning and deploying technological innovations in education services, prompting the education sector to increase investment in related technologies, connect data elements into a data network, and implement collaborative management. The establishment of major scientific facilities and super scientific projects has provided an efficient and intelligent information platform for innovation activities, accelerating the aggregation of economic factors such as talent, capital, and technology (Shang, 2020). Supported by the digital education platform, the time and space limitations of traditional education are broken, and the service mode is transformed from an isolated and linear mode to an interconnected, networked mode, which realizes the free, fast, and effective matching of information among schools, students, parents, and teachers. Further, it promotes the reengineering and optimization of the education service process. According to relevant research, the education services sector will fully leverage advanced information and communication technologies to achieve process innovation, thereby better adapting to its service needs.

At the service upgrading and resource allocation optimization level, the new digital infrastructure stimulates the demand for education and personal capacity enhancement brought about by technological change. It promotes universal access to educational resources (Zeng et al., 2024). The trend of platformization in the education service industry helps establish a learner-centered, intelligent, service-centered platform, which transforms how teachers and students acquire, process, and innovate knowledge. It increases efficiency and reduces the burden of information technology teaching (Ke et al., 2021). At the same time, with the help of multimodal sensory enhancement, body potential perception enhancement, and other technologies, the platform provides learners with a more realistic, experiential, and interactive digital learning environment to meet the personalized learning needs of different levels and fields. The characteristics of information network equality, common sharing, convenience, and speed break the boundaries between inside and outside the school, as well as through the academic system, inside and outside the limitations, truly realizing the maximum breadth of educational resources and fair allocation. Driven by technological progress and new digital infrastructure, the education service industry's production mode and service model have undergone profound changes, with the proportion of high-end education services increasing, promoting the development of the entire industry to a higher level.

Driven by technological progress and new digital infrastructure, the education service industry's production mode and service model have undergone profound changes. Intelligent and personalized services have gradually replaced traditional education services, substantially improving the quality and efficiency of education services. Concurrently, the industrial structure of the education service industry has evolved, with the proportion of middle- and high-end education services increasing, which has promoted the industry's development to a higher level. Based on the above analysis, this paper proposes the following research hypotheses:

Hypothesis 3: New digital infrastructure enhances the TFP of China's education service industry through technological progress.

2.4. The spatial spillover effect of new digital infrastructure on education TFP

The spatial spillover effect of new digital infrastructure on total factor productivity in education can be analyzed from multiple perspectives, including production factors, output outcomes, and economic activities.

In terms of production factors, new digital infrastructure significantly improves the utilization efficiency of production factors by optimizing the allocation and sharing of educational resources. This optimization directly enhances the quality and efficiency of academic services and indirectly promotes the growth of TFP in the education services industry through the effect of externalities. Specifically, with the help of big data analysis, educational institutions can accurately grasp students' learning needs and provide personalized teaching services, thus significantly improving the teaching effect and boosting the TFP.

In terms of output results, promoting and applying new digital infrastructure has accelerated the education services industry's rapid growth, transformation, and upgrading. This change has boosted the TFP of the education services industry itself and, with the help of spatial spillover effects, has positively contributed to the economic growth of other regions, especially neighboring regions. For example, the rise of online education platforms has broken down geographical constraints and promoted cross-regional flow and optimal allocation of educational resources, which has helped narrow the education gap between regions and raise the overall education level.

At the level of economic activities, the new digital infrastructure promotes the integration and synergistic development of the education services industry with other industries by fostering innovation and growth in education services. This integration enhances the TFP of the education services industry and has far-reaching impacts on several aspects, such as labor productivity, industrial structure, consumption, and output through spatial spillover effects. Taking online education platforms as an example, they provide students with a more convenient and efficient learning experience, which significantly enhances their learning ability and employment competitiveness, and drives the vigorous development of online education technology, content production, and other related industries, injecting new vitality into the transformation and upgrading of the education services industry. As a result, this paper proposes research hypothesis 4:

Hypothesis 4: New digital infrastructure has a spatial spillover effect on the TFP of the education service industry.

3. Model, variables and data

3.1. Model

To test Hypothesis 1, the following regression model is developed in this paper to test the association between new digital infrastructure and total factor productivity in China's education service industry:

$$TFP_{it} = \alpha_0 + \alpha_1 DNI_{it} + \alpha_2 control_{it} + v_i + u_t + \varepsilon_{it} \tag{1}$$

where TFP_{it} represents the total factor productivity of the education service industry in province i in year t; DNI_{it} denotes the development level of new digital infrastructure in province i in year t; a series of control variables, v_i and u_t, are the area- and year-fixed effects, respectively; and ε_{it} is an error term.

To test Hypothesis 2 and Hypothesis 3, this paper examines in detail the transmission process of human capital as well as technological progress using a three-step approach:

$$Mediating_{ij} = \beta_0 + \beta_1 DNI_{it} + \beta_2 control_{it} + v_i + u_t + \varepsilon_{it} \tag{2}$$

$$TFP_{it} = \eta_0 + \eta_1 DNI_{it} + \eta_2 Mediating_{ij} + \eta_3 control_{it} + v_i + u_t + \varepsilon_{it} \tag{3}$$

Equation (1) is transformed into Equation (3), which acts as the mediating variable, including human capital and technological progress, and the remaining variables align with those found in Equation (1). The steps for testing are as follows: Initially, assess the significance of α_1. If α_1 is found to be significant, we proceed with the subsequent test. Next, if β_1 is significant, continue with the next test. Ultimately, DNI_{it} and $Mediating_{ij}$ collectively undertake a regression examination on TFP to verify the significance of the coefficients η_1 and η_2 in Equation (3). If η_1 and η_2 are significant and η_1 is smaller than α_1, then we assert that $Mediating_{ij}$ assumes an essential and partially mediating function.

Finally, we use a two-way stationary spatial Durbin model to verify the spatial spillover effect of new digital infrastructure on total factor productivity in China's education services industry:

$$TFP_{ij} = \rho WTFP_{ij} + \gamma WDNI_{ij} + \beta_1 DNI_{ij} + \beta_2 control_{ij} + v_i + u_t + \varepsilon_{it} \tag{4}$$

where ρ is the spatial lagged coefficient of the dependent variable, W denotes the spatial weight matrix, and γ is the spatial lag coefficient of the independent variable, which indicates the effect of the independent variable in neighboring regions on the dependent variable in the area. When $\gamma = 0$ is used, the model degenerates into the SAR model, and when $\rho = 0$ is used, SAR degenerates into the SEM model.

3.2. Variables

3.2.1. New digital infrastructure

Previous studies have primarily relied on single-variable measures such as quasi-natural experiments and fixed-asset investment in the information and communications technology (ICT) sector to assess the development level of new infrastructure at the city or provincial level (Song et al., 2021; Zhang et al., 2022; Chao and Xue, 2023). With the continuous enrichment of the connotation of new digital infrastructure, most scholars have subdivided new digital infrastructure into three core dimensions: information infrastructure, integrated infrastructure, and innovation infrastructure, based on the authoritative definition of new digital infrastructure by the National Development and Reform Commission. They utilize the entropy weight method to calculate a series of indicators to evaluate the development level of digital new infrastructure and its three subsystems (Wu et al., 2020; Zhang, 2024; Gu and Chen, 2024). Building on this foundation, we employ the entropy weight method to evaluate development levels of new digital infrastructure and its subsystems while adopting active enterprise counts in specialized subdomains (Zhang and Sun, 2023) to assess data-scarce sectors.

The information infrastructure dimension covers communication network infrastructure, new technology infrastructure, and computing power infrastructure, focusing on measuring network coverage and computing resource reserves. The convergence infrastructure dimension emphasizes the integration of traditional infrastructure and digital technology, such as digital transformation infrastructure and digital upgrading infrastructure, to assess the depth of technological penetration and the level of industrial synergism. In the innovation infrastructure dimension, it mainly involves the integration of technology, technology and infrastructure, and the integration of traditional infrastructure and digital technology. The dimension of innovation infrastructure mainly involves new types of infrastructure driven by scientific and technological innovation, such as major scientific and technological infrastructure, industrial technological innovation infrastructure, and science and education infrastructure, which play key roles in stimulating innovation and promoting the development of emerging industries. The above data come from the China Torch Statistical Yearbook, the China Science and Technology Statistical Yearbook, the China High-Tech Industry Statistical Yearbook, and statistical yearbooks of provinces and cities.

Among them, enterprise data are sourced from the "Qichacha" platform, data on primary science and technology infrastructure indicators are obtained from the China Science and Technology Resources Sharing Network, industrial technology innovation infrastructure indicator data come from the China Torch Statistical Yearbook, and National University Science Park data are collected from the website of the Ministry of Science and Technology of China. Unless otherwise specified, all other data are sourced from the National Bureau of Statistics, the China City Statistical Yearbook, and various provincial and municipal statistical yearbooks.

3.2.2. Total factor productivity of the educational service industry

This paper applies the dynamic DEA-Malmquist model to measure the total factor productivity of the education service industry in each province. In the construction of the indicator system, drawing on Yang and Xiao (2023), the input indicator aspect focuses on the education factor, and four variables are selected, namely, the number of employed persons in suburban units of the education industry, the total wages of employed persons in suburban units of the education industry, the education expenditure, and the total investment in fixed assets in the education industry. In the output indicator aspect, the number of graduates from general higher education schools (including bachelor's and associate's degrees) and the number of applications and authorizations of China's three kinds of patents are selected as the two variables. Since the education sector was first classified as an independent category (Category P) in the Industrial Classification for National Economic Activities (GB/T 4754-2002) in 2002, systematic provincial-level statistical data became available starting in 2003. Considering that the latest available education expenditure data only extends to 2022 within the research period, this study ultimately sets the analysis timeframe from 2003 to 2022 after evaluating data availability in order to comprehensively assess the total factor productivity of China's provincial education services.

Among them, the number of employed persons and the total wage bill in the education sector are sourced from the China Labour Statistical Yearbook. The total fixed asset investment in the education sector comes from the China Fixed Asset Investment Statistical Yearbook and the China Investment Field Statistical Yearbook. Since the latest edition of the former is the China Fixed Asset Investment Statistical Yearbook 2018, which lacks provincial-level fixed asset investment data for 2018 and beyond, the corresponding figures for 2018–2022 are derived by calculating growth rates from the China Fixed Asset Investment Statistical Yearbook (2019–2023 editions). Unless otherwise specified, all other data are obtained from various editions of the China Statistical Yearbook.

Since the total factor productivity (TFP) calculated using the Malmquist index method reflects relative rates of change to reflect the actual value of TFP in China's education services sector, the above TFP was adjusted based on the research by Li and Deng (2023). Assuming 2003 as the base year (TFP = 1), the index for 2003–2004 is used as the TFP for 2004. The TFP for 2005 is calculated by multiplying the index for 2004–2005 by the TFP for 2004, and so on for the years 2004–2022. In the empirical section that follows, the TFP is represented by the adjusted data as the explanatory variable.

3.2.3. Mediating variables

1. Human capital (edu)

In the context of digital transformation, the structure of human capital is showing a need for skill upgrading. Yang and Jiang (2021) contend that digital economy development drives surging demand for high-skilled labor, particularly interdisciplinary talent. The reason for this trend is that the impact of new digital infrastructure on the total factor productivity of the education service industry is achieved through the effective integration and transformation of technology and educational productivity by improving the human capital elements of key roles in the education system, such as teachers, students, and administrators, in terms of their information technology application capabilities, learning efficiency, and digital management capabilities. Therefore, this paper draws on the study of Yi and Zhou (2018) and uses average years of education as an indicator of human capital. The assigned values for each educational level are set at 1 year for illiteracy, 6 years for elementary school, 9 years for middle school, 12 years for senior high school and junior high school, and 16 years for a higher education level.

2. Technological progress (inn)

Jiang (2021) theoretically explains that the core of new infrastructure projects lies in intangible connections, which break down the boundaries between virtual space and physical space. From the perspectives of industrial structure optimization and technological progress, these projects have enhanced the production efficiency of the service industry. With the rapid development of internet technology, the supply-demand model of the education service industry has undergone a fundamental transformation. On the supply side, diverse online classrooms enable people to access education services through the internet and mobile apps conveniently. On the demand side, the education service needs of different groups and stages can be precisely matched through internet platforms, finding common ground, significantly improving the efficiency of supply-demand matching, and effectively driving the education service industry toward a higher level of supply-demand balance. Therefore, this paper draws on the research approach of Liu (2023) and uses the number of effective invention patents of industrial enterprises above the scale as a measurement indicator to further explore its impact on the development of the education service industry.

3.2.4. Control variables

Given the complexity of the factors influencing the development of the education service industry, to obtain accurate measurement results and reduce the measurement error due to the model setting, relevant control variables are added to the model, following the methodology outlined by Xia and Xiao (2019), Sun and Zhu (2024), Zheng and Cai (2019), and Yang and Xiao (2023), etc. The control variables are defined as follows: industrial structure (ind), expressed as the value added of the tertiary industry as a percentage of the local GDP in the year (%); R&D intensity (rd), described as the intensity of R&D investment in research and experimental development (rd) in each province (%); the level of economic development (rgdp), measured as the per capita GDP in each province (RMB 10,000 yuan); the scale of technology market development (mark), measured by the transaction volume of regional technology markets (billion yuan); financial supply (gov), expressed by selecting the proportion of funds from government expenditure in education expenditure; urbanization level (urb), measured by the ratio of the urban population to the total population of each province (%); and foreign trade dependency (ftd), expressed as the ratio of total imports and exports (based on the location of the business entity) to the regional gross domestic product (%).

3.3. Data

This paper is based on the panel data of all provinces and cities in China from 2004 to 2022 for empirical analysis. Due to the more serious missing data issues in Hong Kong, Macao, and parts of the Tibet Autonomous Region, these regions are excluded, and the remaining 30 provinces, municipalities, and autonomous regions in China are selected as the research objects. For provinces, municipalities, and cities with only sporadic missing data in individual years, interpolation is used to supplement the data. All variables are summarized as follows Table 1.

Table 1. Variable definition table.

Category	Name	Symbol	Measurement method	Source
Explanatory variable	New digital infrastructure	NDI	Calculated using the entropy weight method based on three aspects: information infrastructure, convergence infrastructure, and innovation infrastructure.	Measured
Explained variable	Total factor productivity of the education service industry	TFP	Calculated using the DEA-Malmquist model	Measured
Mediating variables	Human capital	edu	Average years of education per capita	China Statistical Yearbook
	technological progress	inn	Number of valid invention patents held by large-scale industrial enterprises	China Statistical Yearbook
Control variables	Industrial structure	and	Added value of the tertiary industry / GDP	China Statistical Yearbook
	R&D intensity	rd	Intensity of R&D expenditure	China Science and Technology Statistical Yearbook
	Level of economic development	rgdp	Per capita GDP	China Statistical Yearbook
	The scale of technology market development	mark	Technology market transaction volume	China Statistical Yearbook
	Financial supply	gov	Education expenditure/government expenditure	China Statistical Yearbook
	Urbanization level	urb	Urban population/total population	China Statistical Yearbook
	Foreign trade dependency	ftd	Total imports and exports/GDP	Import and export data sourced from the General Administration of Customs, GDP sourced from the China Statistical Yearbook

4. Baseline regression

4.1. Descriptive statistics

Descriptive statistics for each variable are presented in Table 2 below. The TFP of the education services industry exhibits notable dispersion characteristics: the maximum value is 5.910, the minimum is 0.791, the mean is 1.694, and the standard deviation is 0.809, indicating relatively low TFP levels in China's education sector with significant room for improvement. The new digital infrastructure index shows even greater dispersion, with a maximum of 0.9407, a minimum of 0.0001, and a standard deviation of 0.1922, reflecting substantial regional disparities in digital infrastructure development. Other variables also demonstrate wide gaps between their maximum and minimum values. To further verify whether there is multicollinearity, this paper examines the variance inflation factor between variables. According to the data, Mean VIF = 3.9, and the VIF values of each variable are less than 10, indicating that there is no serious multicollinearity between variables.

Given the potential for heteroscedasticity and frequent data fluctuations in the sample, logarithmic transformations were uniformly applied to all control and mediating variables in this study to mitigate their impact on the empirical results.

Table 2. Descriptive statistics.

Variables	Mean	SD	Min	Max
TFP	1.694	0.809	0.791	5.910
NDI	0.2737	0.1922	0.0001	0.9407
ind	44.73	9.915	27.41	83.87
rd	1.553	1.125	0.178	6.830
rgdp	4.689	3.170	0.421	19.03
mark	267.0	599.1	0.184	5286
gov	16.19	2.580	9.894	22.22
urb	55.08	15.06	15.66	89.60
ftd	30.77	35.52	0.763	171.2
edu	8.907	1.046	6.378	12.78
inn	20,017	53,083	7	572,589

4.2. Baseline results

Next, a baseline regression analysis is conducted on the panel data of 30 provinces, and the Husman test is used to determine the optimal regression model. The statistical value of the Husman test is 17.06, rejecting the null hypothesis at the 5% significance level, indicating that the fixed-effects model is more appropriate than the random-effects model. Therefore, we selected the fixed-effects model to perform regression on Equation (1). To avoid the influence of individual differences across regions and year-to-year variations, a two-way fixed model incorporating individual effects and time effects is employed for the baseline regression.

Column (1) shows regression results without control variables, where the coefficient of new digital infrastructure on education services TFP is 1.513, significant at the 1% level, indicating a positive promoting effect. Columns (2)–(6) progressively include control variables, with NDI coefficients remaining positive and statistically significant at the 1% level, further validating Hypothesis 1 that NDI development positively affects education TFP. From the perspective of the actual needs of China's education service industry, new digital infrastructure centered on the Internet of Things, artificial intelligence, blockchains, and high-speed information networks is profoundly restructuring the underlying technical architecture and resource allocation logic of education services, providing a new source of momentum for the improvement of TFP in China's education service industry.

Table 3. Baseline regression results.

Variables	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP	(6) TFP	(7) TFP	(8) TFP
NDI	1.513***	1.522***	1.560***	1.357***	1.431***	1.456***	1.556***	1.524***
	(5.034)	(5.062)	(5.208)	(4.633)	(4.760)	(4.800)	(5.108)	(4.983)
lnind		0.263	0.215	−0.345	−0.306	−0.285	−0.212	−0.204
		(0.963)	(0.791)	(−1.222)	(−1.075)	(−0.995)	(−0.739)	(−0.711)
lnrd			0.308**	0.319***	0.306**	0.315***	0.365***	0.387***
			(2.505)	(2.665)	(2.551)	(2.604)	(2.994)	(3.129)
lnrgdp				−0.820***	−0.771***	−0.755***	−0.655***	−0.588***
				(−5.70)	(−5.112)	(−4.926)	(−4.155)	(−3.464)
lnmark					−0.034	−0.034	−0.026	−0.023
					(−1.090)	(−1.089)	(−0.834)	(−0.736)
lngov						−0.182	−0.198	−0.199
						(−0.639)	(−0.699)	(−0.703)
lnftd							−0.166**	−0.160**
							(−2.474)	(−2.372)
lnurb								−0.235
								(−1.067)
Constant	0.949***	−0.131	−0.354	2.883**	2.881**	3.243**	3.530***	4.271***
	(6.450)	(−0.116)	(−0.313)	(2.333)	(2.332)	(2.385)	(2.599)	(2.800)
Observations	570	570	570	570	570	570	570	570
area	YES	YES	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES	YES	YES

Note: (t-statistics are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. This is the same for subsequent tables.)

4.3. Robustness tests

4.3.1. Replacement of core explanatory variables

1. Replacement of the indicator system

In order to ensure the reliability of the research findings, this study constructs an alternative measurement system for robustness testing. Based on the research framework of Wu et al. (2020), the sum of fixed asset investment in information infrastructure, integrated infrastructure, and innovation infrastructure is chosen as the replacement variable for new digital infrastructure (new_NDI). According to column (1) of Table 4, after replacing the core explanatory variables, the coefficient of new digital infrastructure still passes the significance test at the 1% level, further confirming the robustness of the conclusion that new digital infrastructure has a direct positive impact on TFP of the education services industry, and strongly verifying Hypothesis 1 of this paper again.

2. One-period lag representation

In order to further verify the robustness of the research results, this paper introduces the new digital infrastructure lag (L_NDI) variable for regression analysis. By introducing explanatory variables lagged by one period, this paper somewhat weakens the immediate feedback mechanism that may exist between the explanatory variables and the explained variables in the current period, thus reducing the estimation bias caused by endogeneity and enhancing the reliability of the regression results. According to column (2) of Table 4, even after considering the time lag effect of new digital infrastructure, its impact on the TFP of the education service industry is still significantly contributing and has a certain degree of robustness.

Table 4. Robustness tests.

Variables	(1) TFP	(2) TFP	(3) TFP	(4) GMM
new_NDI	0.230^{***}			
	(6.308)			
L_NDI		0.706^{**}		
		(2.038)		
L_TFP				0.916^{***}
				(0.043)
NDI			1.537^{***}	0.788
			(4.961)	(0.600)
lnind	-0.616^{***}	−0.200	−0.214	−0.095
	(−2.174)	(−0.630)	(−0.747)	(0.687)
lnrd	0.254^{**}	0.364^{***}	0.355^{***}	−0.050
	(2.065)	(2.916)	(2.890)	(0.188)
lnrgdp	-1.019^{***}	−0.107	-0.589^{***}	0.036
	(−5.954)	(−0.539)	(−3.416)	(0.537)
lnmark	−0.027	0.005	−0.043	−0.007
	(−0.878)	(0.155)	(−1.388)	(0.071)
lngov	0.026	−0.048	−0.163	−0.041
	(0.093)	(−0.175)	(−0.585)	(0.363)
lnftd	-0.110^{*}	−0.108	-0.169^{**}	0.078
	(−1.669)	(−1.609)	(−2.428)	(0.091)
lnurb	-0.528^{**}	-2.296^{***}	−0.150	−0.998
	(−2.416)	(−5.372)	(−0.661)	(2.814)
Constant	4.671^{***}	11.207^{***}	3.558^{**}	4.666
	(3.391)	(6.068)	(2.570)	(10.478)
Observations	570	540	570	540
area	YES	YES	YES	YES
year	YES	YES	YES	YES

4.3.2. Winsorization

This paper uses the shrinkage treatment for robustness testing to examine the model's sensitivity to extreme values. The regression results, as shown in column (3), reveal that the coefficient of new digital infrastructure after Winsorization is 1.537, which is significantly positive at the 1% level. This indicates that the core conclusions of this study are not dependent on extreme values and that new digital infrastructure still has a significant positive effect on the growth of TFP in the education services industry, demonstrating the model's strong robustness.

4.3.3. System GMM analysis

This study employs 19-year panel data from 30 Chinese provinces. Due to the short time span of the sample and the large number of cross-sectional units, such short-term dynamic panel data often suffer from endogeneity issues. Although the relationship between NDI and TFP in the education service industry has been preliminarily addressed through the introduction of a two-way fixed effects model and control variables, this study additionally uses the generalized method of moments (GMM) method for verification to ensure the reliability of the research conclusions. This method builds upon the original model by adding a lagged term of the dependent variable (L_TFP) and constructing a system GMM model using instrumental variables. The regression results of the model are shown in column (4) of Table 4.

In the test for serial correlation, the significance level of AR(1) is 0.006, and the P-value of AR(2) reaches 0.572, indicating that the disturbance term in the model does not exhibit second-order serial autocorrelation. In addition, the P-value of the Hansen over-identification test is 0.334, indicating that the instrumental variables selected in this study are reasonable and practical. According to the results in column (4), the lagged term of the explained variable and the regression coefficient of NDI are both significant, further verifying the conclusion that the new digital infrastructure has a positive effect on the total factor productivity of the education service industry.

5. Mechanism test

5.1. The mediating effect of human capital

After constructing a theoretical framework, we empirically verified the channels. Through the derivation and analysis of the theory, Hypothesis 2 proposes that new digital infrastructures can realize the all-important productivity of the education service industry by increasing the stock of human capital and promoting technological innovation. We used a three-step approach to examine the transmission process of this mechanism in detail.

At present, the rapid development of digital infrastructure has provided unprecedented opportunities for the widespread dissemination and efficient utilization of educational resources. The improvement of these infrastructures not only promotes the balanced distribution of educational resources but also enhances the intelligence and personalization of teaching and learning, thereby contributing to the overall improvement of the quality of the workforce, i.e., human capital. The enhancement of educational human capital means that the workforce possesses higher levels of knowledge, stronger learning abilities, and greater innovation capabilities, which directly impact the production efficiency and innovation capabilities of the education industry. Additionally, educational human capital is one of the core elements of the development of the education industry. A high-quality workforce can make more effective use of educational resources, improve the quality and efficiency of educational services, and thereby promote the improvement of total factor productivity in education.

Therefore, this paper selects human capital as an intermediate variable to test the mediating effect between new digital infrastructure and the total factor productivity of the education service industry. The results are shown in Table 5.

Table 5. Human capital channel test.

Variables	(1) TFP	(2) lnedu	(3) TFP
NDI	1.524***	0.145*	1.386***
	(4.983)	(1.660)	(4.692)
lnedu			0.952***
			(6.418)
lnind	−0.204	−0.120	−0.089
	(−0.711)	(−1.466)	(−0.322)
lnrd	0.387***	0.076**	0.315***
	(3.129)	(2.136)	(2.632)
lnrgdp	−0.588***	−0.028	−0.561***
	(−3.464)	(−0.582)	(−3.431)
lnmark	−0.023	−0.000	−0.023
	(−0.736)	(−0.006)	(−0.763)
lngov	−0.199	0.037	−0.235
	(−0.703)	(0.456)	(−0.859)
lnftd	−0.160**	0.005	−0.165**
	(−2.372)	(0.266)	(−2.538)
lnurb	−0.235	−0.237***	−0.010
	(−1.067)	(−3.753)	(−0.045)
Constant	4.271***	3.391***	1.044
	(2.800)	(7.760)	(0.672)
area	YES	YES	YES
year	YES	YES	YES

The results related to the human capital channel are displayed in Table 5. In the regression analysis of the model (1), the coefficient of new digital infrastructure is 1.524. It is significant at the 1% level, which indicates that the development of new infrastructure has a positive promotion effect on the TFP of education services. Further examining the results of model (2), the regression coefficient of new digital infrastructure on human capital is 0.145 and is significant at the 5% level, confirming that new infrastructure has a positive promotional effect on human capital. Model (3) results show that the regression coefficient of human capital on TFP of educational services is 0.952, also significant at the 1% level, indicating that human capital has a positive promoting effect on the development of educational services. The three-step regression results demonstrate the mediating role of human capital in NDI's promotion of education TFP, confirming Hypothesis 2 that NDI enhances education quality through human capital development.

5.2. The mediating effect of technological progress

The rapid advancement of new digital infrastructure creates unprecedented opportunities for enhanced dissemination and utilization efficiency of educational resources. These developments not only promote equitable resource distribution but also elevate instructional intelligence and personalization, thereby facilitating human capital accumulation. The improvement of educational human capital means that the workforce has a higher level of knowledge, stronger learning abilities, and greater innovation capabilities, which has a direct impact on the productivity and innovation capabilities of the education industry. Crucially, as a core production factor, refined human capital optimizes educational resource utilization, improves service quality and efficiency, and ultimately promotes the improvement of TFP in education. Consequently, this study employs human capital as a mediating variable. The results are shown in Table 6.

Table 6. Technological progress channel test.

Variables	(1) TFP	(2) lninn	(3) TFP
NDI	1.524***	0.636*	1.467***
	(4.983)	(1.775)	(4.803)
lninn			0.090**
			(2.411)
lnind	−0.204	0.235	−0.225
	(−0.711)	(0.700)	(−0.788)
lnrd	0.387***	0.315**	0.358***
	(3.129)	(2.175)	(2.899)
lnrgdp	−0.588***	0.569***	−0.639***
	(−3.464)	(2.863)	(−3.755)
lnmark	−0.023	−0.071*	−0.017
	(−0.736)	(−1.924)	(−0.533)
lngov	−0.199	0.438	−0.239
	(−0.703)	(1.318)	(−0.845)
lnftd	−0.160**	0.238***	−0.181***
	(−2.372)	(3.011)	(−2.679)
lnurb	−0.235	−0.208	−0.217
	(−1.067)	(−0.803)	(−0.986)
Constant	4.271***	4.215**	3.890**
	(2.800)	(2.358)	(2.548)
area	YES	YES	YES
year	YES	YES	YES

The results related to the technological progress channel are displayed in Table 6. In the regression analysis of the model (1), the coefficient of new digital infrastructure is 1.524, which is significant at the 1% level, indicating that the development of new infrastructure has a positive promoting effect. Further examining the results of the model (2) analysis, the regression coefficient of new digital infrastructure on human capital is 0.636. It is significant at the 5% level, confirming that new infrastructure positively promotes technological progress. Model (3) results show that the regression coefficient of technological progress on TFP of educational services is 0.090, also significant at the 5% level, indicating that technological progress has a positive promoting effect on the development of educational services, confirming Hypothesis 3.

6. Heterogeneity analysis

6.1. Regional heterogeneity analysis

China is a vast country, and different regions exhibit significant differences in terms of resource endowments, industrial structure, and economic development. To study the possible regional differences and the impact of new digital infrastructure on the TFP of the education service industry, this paper divides the sample data into three regions: Eastern, Central, and Western, for analysis based on the standards set by the National Bureau of Statistics. Through empirical research in different areas, it is possible to more accurately capture the impact mechanism and degree of new digital infrastructure on the TFP of the education service industry in various regions, thereby providing a scientific basis for the formulation of regional differentiation policies. The regression results are shown in Table 7.

Table 7. Regional heterogeneity analysis.

	Eastern	Central	Western
NDI	1.934**	−1.115***	−1.107***
	(2.026)	(−3.192)	(−4.064)
lnind	0.716	−0.604***	0.069
	(0.868)	(−2.733)	(0.300)
lnrd	−0.203	0.284**	0.322***
	(−0.570)	(2.209)	(3.342)
lnrgdp	−0.068	−0.298*	0.437***
	(−0.164)	(−1.851)	(2.782)
lnmark	−0.057	−0.051	−0.002
	(−0.511)	(−1.643)	(−0.078)
lngov	−1.379*	−0.746**	−0.315
	(−1.797)	(−2.583)	(−1.478)
lnftd	−0.430	0.143*	0.120***
	(−1.224)	(1.965)	(2.884)
lnurb	0.755	−0.722***	−0.212
	(1.516)	(−3.154)	(−1.081)
Constant	1.121	7.724***	2.464**
	(0.265)	(6.579)	(1.990)
Observations	209	152	209
area	YES	YES	YES
year	YES	YES	YES

The data reveal significant regional differences in the impact of the new digital infrastructure on education services' TFP. In eastern regions, new digital infrastructure significantly positively affects education services development at the 1% level. In contrast, central and western regions exhibit negative coefficients, which are also significant at 1%, indicating an inhibitory effect. The main reasons are as follows.

The eastern region has demonstrated a significant positive effect on the TFP of the education service industry through new digital infrastructure. As the pioneer of economic reform, the East region boasts robust economic strength, strategic geography, technological accumulation, and market maturity to develop advanced digital systems. These provide comprehensive financial, technological, and human capital foundations for educational advancement. The region's competitive education sector further integrates digital infrastructure to accelerate intelligent and personalized transformations, substantially enhancing instructional quality and efficiency. In contrast, the negative impact of new digital infrastructure in the central and western regions reflects the structural imbalance between technology application and regional carrying capacity. On the one hand, the digital transformation of the education service industry in the central and western regions faces the contradiction of hardware advancement outpacing software development. Although new digital infrastructure has rapidly laid the groundwork for information networks, smart devices, and other infrastructure in the short term, soft investments such as teacher training, digital adaptation of course content, and restructuring of education management processes have not been able to keep pace. On the other hand, the scale and structure of the education market in the central and western regions limit the effectiveness of digital technology. The low population density and weak educational consumption capacity of the central and western regions make it difficult for online education platforms and innovative campus systems to achieve economies of scale, resulting in high fixed cost-sharing pressure and longer investment return cycles for enterprises, which makes it challenging to convert investments in new digital infrastructure into sustainable productivity gains.

Currently, the eastern region is in a stage of deepening technological integration, with new digital infrastructure driving process reengineering and model innovation in the education service industry, while the central and western regions are still in the early stages of technological penetration. The characteristics of new digital infrastructure are not sufficiently compatible with the local education ecosystem, which may lead to resource allocation distortions or technological substitution shocks in the short term. Therefore, the negative coefficient does not necessarily mean that new digital infrastructure is ineffective but more likely reflects the phased bottlenecks in the central and western regions in terms of technological digestion capacity and institutional adaptation capacity. Resolving this contradiction requires differentiated policies. The central and western regions need to prioritize human capital and institutional innovation in order to achieve dynamic adaptation between new digital infrastructure and the education system.

6.2. Analysis of infrastructure type heterogeneity

Considering that different types of new infrastructure may have other impacts on the high-quality development of the education service industry, we further divide them into three types: integrated infrastructure, information infrastructure, and innovation infrastructure, and examine the differences in the effects of different infrastructure types. The regression results are shown in Table 8.

The study found that the estimated coefficient for information infrastructure is 4.820, for integrated infrastructure is 6.244, and for innovation infrastructure is 3.339, all of which passed the significance test at the 1% level. It can be concluded that different types of infrastructure have varying effects on promoting total factor productivity in the education services sector, ranked from highest to lowest as follows: integrated infrastructure, information infrastructure, and innovation infrastructure. This variation is closely related to the characteristics of each infrastructure type and their degree of integration with the education services sector.

Table 8. Infrastructure type heterogeneity.

	Information	Integration	Innovation
NDI	4.820***	6.244***	3.339***
	(5.105)	(5.031)	(4.772)
lnind	−0.204	−0.207	−0.208
	(−0.714)	(−0.723)	(−0.724)
lnrd	0.379***	0.396***	0.386***
	(3.071)	(3.205)	(3.116)
lnrgdp	−0.586***	−0.588***	−0.595***
	(−3.454)	(−3.469)	(−3.498)
lnmark	−0.025	−0.022	−0.021
	(−0.803)	(−0.699)	(−0.670)
lngov	−0.201	−0.201	−0.191
	(−0.709)	(−0.708)	(−0.671)
lnftd	−0.157**	−0.163**	−0.158**
	(−2.343)	(−2.412)	(−2.342)
lnurb	−0.235	−0.237	−0.238
	(−1.068)	(−1.076)	(−1.078)
Constant	3.824***	3.842***	3.816***
	(2.743)	(2.755)	(2.728)
Observations	570	570	570
area	YES	YES	YES
year	YES	YES	YES

Integrated infrastructure emphasizes the organic combination of traditional infrastructure and digital technologies, which can more directly break down barriers across various segments of education services, enhancing the sector's intelligence and efficiency. Information infrastructure primarily focuses on constructing communication networks, data centers, and similar facilities, indirectly improving the efficiency of education services by optimizing information flow and reducing operational costs. However, its promotion of the total factor productivity of the education service industry is mainly achieved indirectly through technological empowerment. Compared with the direct integration effect of integrated infrastructure, its impact is slightly weaker. Innovation infrastructure drives technological innovation and quality improvement in education by providing cutting-edge research facilities and technical services. However, the application of these technologies in the education sector is still in the exploratory and pilot stages, with relatively low technological maturity and market penetration, resulting in a comparatively weaker promotional effect among the three infrastructure types. Overall, this difference reflects the varying stages of application and integration of infrastructure at different levels in the digital transformation of China's education service industry. As innovative technologies continue to mature and spread, the potential for innovative infrastructure to boost total factor productivity in the education service industry is expected to be further realized in the future.

7. Spatial spillover effect

7.1. Spatial correlation tests

This paper uses a spatial weight matrix based on geographic distance. The distance between two regions is calculated using their latitude and longitude coordinates, and the reciprocal of this distance is used as the weight value, thereby establishing the inverse distance spatial weight matrix. The global Moran index test is conducted on the whole factor index of China's education service industry to verify whether spatial autocorrelation occurs, and the results are shown in Table 9.

Table 9. Global Moran I statistics for education services TFP.

Year	Moran I	Z-statistic	P-value
2004	−0.060	−0.266	0.395
2005	0.116	1.570	0.058
2006	0.004	0.397	0.346
2007	0.027	0.641	0.261
2008	0.152	1.955	0.025
2009	0.225	2.864	0.002
2010	0.219	2.969	0.001
2011	0.192	2.743	0.003
2012	0.199	2.881	0.002
2013	0.185	2.665	0.004
2014	0.207	2.919	0.002
2015	0.204	2.929	0.002
2016	0.201	2.907	0.002
2017	0.231	3.189	0.001
2018	0.224	3.103	0.001
2019	0.206	2.904	0.002
2020	0.209	2.891	0.002
2021	0.199	2.781	0.003
2022	0.188	2.717	0.003

From the table, there have always been positive values since 2005 and significantly positive values after 2008. This indicates a significant positive spatial correlation in the total factor productivity of China's education services industry, i.e., highly efficient provinces tend to be adjacent to equally efficient provinces. It is worth noting that the non-significant Moran index for the three years of 2004, 2006, and 2007 does not indicate that there is no spatial correlation. It may be that the correlation exists only in some regions, or it may be that there is a positive and negative offset between regions (Long et al., 2024).

7.2. Spatial regression and effects decomposition

According to Moran's index, the explanatory variables exhibit some spatial autocorrelation, which can be accounted for by building a spatial measurement model. This paper applies the LM test, the Hausman test, and the LR test to make the results more accurate, and according to the test results, the SDM model with fixed effects is used. Spatial regression was performed using Equation (4), and the results are shown in Table 10.

Table 10 presents the regression results for the spatial effects. As can be seen from the table, the spatial autoregressive coefficient is 0.498. It is significant at the 1% level, indicating that the total factor productivity of the education service industry has a positive spatial spillover effect on itself. When one province progresses in developing the education service industry, its neighboring provinces may show a rise in data comparison due to knowledge spillover, resource sharing, or collaborative innovation. In the main effect, the coefficient of the explanatory variable, the new digital infrastructure level, is 1.255. It is significantly positive at the 1% level, indicating that the construction of new digital infrastructure can effectively promote the total factor productivity of the education service industry.

Table 10. Spatial spillover effects.

	Main	Spillover effect	Decomposition effects of spillovers		
			direct effect	indirect effect	aggregate effect
NDI	1.255 ***	2.235***	1.578***	5.456***	7.034***
	(4.196)	(2.637)	(4.344)	(2.795)	(3.189)
lnind	−0.405*	−0.259	−0.485**	−0.946	−1.431
	(−1.700)	(−0.360)	(−2.004)	(−0.651)	(−0.888)
lnrd	0.332 ***	0.722***	0.444***	1.763***	2.207***
	(3.303)	(3.029)	(3.452)	(2.984)	(3.231)
lnrgdp	0.671 ***	1.610***	0.900***	3.719***	4.618***
	(4.000)	(3.983)	(4.376)	(3.780)	(4.222)
lnmark	−0.145 ***	−0.246***	−0.189***	−0.635***	−0.824***
	(−4.122)	(−3.169)	(−4.233)	(−3.406)	(−3.852)
lngov	0.217	−0.235	0.223	−0.017	0.206
	(0.985)	(−0.370)	(0.992)	(−0.014)	(0.158)
lnftd	0.077	0.041	0.088	0.170	0.258
	(1.095)	(0.225)	(1.013)	(0.440)	(0.570)
lnurb	−0.906***	−2.005**	−1.202***	−4.657***	−5.859***
	(−3.245)	(−2.566)	(−3.763)	(−2.909)	(−3.316)
rho	0.498***				
	(7.156)				
N	570				

According to the spatial effect, it can be seen that the direct and indirect effects of new digital infrastructure on the TFP of the education service industry are both positive and significant at the 1% level, indicating that the development of the education industry in this region is not only facilitated by the development of the new digital infrastructure in this region but also positively affected by the development of the new digital infrastructure in the neighboring regions, which proves that the construction of the new digital infrastructure on the TFP of the education service industry has a spatial spillover effect. Observing the size of the coefficient, it is found that the direct effect coefficient of new digital infrastructure on the TFP of the education service industry is 1.578, and the indirect effect coefficient is 5.456, indicating that the promotion effect of new digital infrastructure on the TFP of the education service industry in the neighboring regions is greater than that of the province, which can increase the investment in new digital infrastructure, give full play to the spatial radiation effect of new digital infrastructure, and promote the high-quality development of China's education service industry. Comparing the main effect and the total effect, it can be seen that if the spatial interaction is ignored, the pulling effect of new digital infrastructure on the development of the education service industry will be underestimated, again verifying the reasonableness of using the spatial model in this paper.

From an economic operations perspective, the positive spatial spillover effects in educational TFP fundamentally stem from interregional knowledge diffusion and factor mobility. When a province enhances educational efficiency through digital teaching platforms or vocational education reforms, its innovative practices spread to neighboring provinces via channels such as teacher mobility, academic exchanges, and the sharing of MOOC resources, creating a cross-regional learning effect akin to "learning by doing".

Crucially, digital infrastructure's indirect effects on educational TFP substantially exceed direct effects, revealing the network externality characteristics of digital infrastructure. When a province builds a regional education cloud platform, neighboring provinces can access and use it without repeated investment. This free-rider effect reduces marginal costs as coverage expands, exemplified by Guizhou's big data center providing cost-effective data storage and analytics for surrounding regions, collectively elevating regional digital education capacity.

It can thus be seen that if spatial interaction effects are ignored, traditional non-spatial models will underestimate the actual contribution rate of new digital infrastructure. This explains why investment in new educational infrastructure needs to break through administrative boundaries and shift to regional collaborative planning.

8. Conclusions and discussion

8.1. Conclusions

Based on China's upgraded panel data from 2004 to 2022, this study explores the impact and mechanism of new digital infrastructure on the total factor productivity of education services at both the theoretical and empirical levels. The level of new digital infrastructure development significantly impacts China's education output, which remains valid after robustness testing. The mechanism test shows that new digital infrastructure enhances the total factor productivity in the education service industry at the provincial level by strengthening human capital and accelerating technological progress. There is significant regional heterogeneity in the process of new digital infrastructure promoting the development of total factor productivity in China's education service industry. All three types of infrastructure have a significant direct promotion effect on the all-important productivity of the education service industry. However, there is a big difference in the degree of influence, in descending order of integrated, information, and innovation infrastructure. Further analysis reveals that there is a spatial spillover effect of new digital infrastructure on the improvement of total factor productivity in the education services industry.

8.2. *Policy recommendations*

The study offers several important implications for policymakers.

1. The government should play a guiding role. On the one hand, it should focus on innovation in key areas and weak links of new infrastructure to integrate key technologies and core equipment to overcome "bottleneck" challenges. Taking big data centers as an example, the government should introduce policies to enhance the overall planning and factor coordination of data centers and data resources, thereby supporting the education service industry in accelerating the development of new business forms and models. On the other hand, the government should increase investment in new digital infrastructure, give full play to the government's guiding role, formulate preferential policies on taxation, finance, and other aspects related to investment in new digital infrastructure, and encourage and guide social capital to participate in the investment and operation of new digital infrastructure.
2. A regional differentiated strategy should be established. The eastern region should rely on national computing power hubs, prioritize the layout of educational big data centers and innovative platforms, learn from the experience of areas such as the Yangtze River Delta to establish cross-regional data sharing mechanisms, deepen university-enterprise integration, and allocate part of the computing power to the central and western regions. The central region should leverage the locational advantages of the "East Data West Computing" network backbone nodes, build regional educational cloud computing centers, develop characteristic educational projects matching local industries, and promote resource sharing among universities within the region. The western region should make full use of the policy dividends of the "East Data West Computing" project, prioritize the layout of educational digital infrastructure in national computing power hubs such as Chengdu-Chongqing and Guizhou, develop distance education and ethnic characteristic projects, establish a long-term counterpart support mechanism between the east and west, and promote the balanced allocation of educational resources.
3. Efforts should be made to promote the differentiated development of integrated, informational, and innovative infrastructure, enhancing their empowerment capabilities. In terms of integrated infrastructure, efforts to promote the intelligent transformation of transportation facilities, optimize the network through digital technologies, and improve the flow efficiency of educational resources should be made. In terms of information infrastructure, accelerate the layout of 5G base stations, deepen coverage in the central and western regions, promote the application of the Internet of Things in educational scenarios, and upgrade backbone and metropolitan area networks. In terms of innovative infrastructure, give full play to the leading role of major scientific and technological infrastructure, establish cross-regional collaborative clusters of major scientific and technological facilities, and build many industrial technology innovation centers and innovation research institutes focused on high-tech industries and strategic emerging industries to help breakthroughs in key technologies and fundamental theories in the education service field.
4. Talent cultivation and introduction should be strengthened, which involves enhancing the construction of talent teams, building a sound cultivation system, deepening education reform, and optimizing the regional structure. Promote industry-university-research cooperation to cultivate composite talents, strengthen talent introduction, improve policies and service systems, attract high-level talents at home and abroad, and enhance the diversity and internationalization of talents.
5. Strengthen technological interaction and complementarity to promote the digital transformation of the education service industry. Promote the integration of new digital

infrastructure and educational technologies and popularize new educational models such as innovative education. Promote the integration of cloud computing, artificial intelligence, and the Internet of Things with education, build cloud platforms, achieve intelligent recommendation and cross-time-space resource sharing, and improve the quality and efficiency of education.

8.3. Shortcomings and prospects

Based on the current development status of new digital infrastructure and TFP in the education service industry, this paper reveals the mechanism of digital infrastructure's impact on TFP in the education service industry through theoretical analysis and empirical testing. Although the study has made up for the shortcomings of existing literature to a certain extent, the following limitations still exist:

First, new digital infrastructure covers a wide range of areas and is developing rapidly, with its concepts and connotations constantly evolving. When measuring its construction level, it is difficult for this study to cover all elements comprehensively. Due to limitations in data acquisition and research methods, only some typical indicators were selected to construct the evaluation system, resulting in an incomplete portrayal of the development level of new digital infrastructure, which may not fully reflect its overall role in the education service industry. Second, this study primarily uses provincial-level macro data for empirical analysis, which can reflect regional trends but does not delve into the characteristics of different types of educational institutions or disciplines. This limits the completeness and depth of the research conclusions and restricts their guidance value for policy differentiation design.

In response to the above shortcomings, future research can be deepened and expanded in the following directions. On the one hand, we can actively explore a more comprehensive and scientific measurement system for new digital infrastructure, combine the innovative application of digital technologies such as artificial intelligence, big data, and blockchains in the field of education, continue to explore new data sources, supplement and improve relevant indicators and improve the accuracy and comprehensiveness of the assessment of the development level of new digital infrastructure. On the other hand, future research can delve deeper into the city level and even the enterprise level to explore the differences in the impact and role of new digital infrastructure on education service enterprises of different sizes and types, providing a more accurate theoretical basis for the formulation of differentiated education digitalization development policies and enterprise strategies.

Author contributions

Lanli Hu: Conceptualization, investigation, supervision, draft writing, and funding acquisition. Yaqi Gong: Investigation, data collection, and original draft writing and editing. Lu Zhu: Methodology, data analysis, result interpretation, validation, and funding acquisition.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in creating this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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