International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 17 (2025) pp. 1-16

https://doi.org/10.70917/ijcisim-2025-0238
Article

Analysis of the Promotion Effect of Vocational Undergraduate Innovative Practice Teaching on New Quality Productivity under Artificial Intelligence-Enabled Industry-Teaching Integration Model

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Research Project of Zhejiang Federation of Humanities and Social Sciences, 25HQZZ083YB, A Study on the Construction of Entrepreneurial Risk Awareness Indicators for Dual-Innovation Education of Vocational College Students in Zhejiang Province

Abstract: Based on the background of AI-enabled industry-education integration, this paper investigates the promotion impact between vocational undergraduate innovative practice teaching and new quality productivity. Firstly, the evaluation index system of undergraduate innovative practice teaching and new quality productivity is constructed, the entropy value method is used to comprehensively evaluate the development level of new quality productivity in 30 provinces in China from 2014 to 2024, and the kernel density estimation is used to measure the regional differences in the level of undergraduate innovative practice teaching. Finally, the quantile regression model was used to regress the three dimensions of undergraduate innovative practice teaching and new quality productivity. The results show that the regional balance of undergraduate innovative practice teaching development is enhanced, the mean value of undergraduate innovative practice teaching in central region is 0.2671 in 2014-2024, the lowest level of development, and the differences in western provinces tend to expand and polarization phenomenon occurs; the development of new-quality productivity in high-level counties has the most significant spatial spillover effect; under quantile regression , the promotion effect of undergraduate innovative practice teaching on the new quality productivity shows a U-shaped change.

Keywords: new quality productivity; kernel density estimation; regional differences; entropy weight method

1. Introduction

As a new kinetic energy driving the rapid development of China's economy and technology, the new quality productivity is gradually becoming the focus of attention of all walks of life, which takes innovation as the core driving force, and is an advanced form of productivity integrating high-tech, high-efficiency and high-quality [1-2]. With the promotion of "double high program", higher vocational education is shifting from scale expansion to connotative development. As the strategic direction of vocational education reform, the integration of industry and education requires the practical teaching mode to break through the traditional classroom boundaries and realize the organic connection between the education chain and the industrial chain [3-4]. The continuous development trend of artificial intelligence puts forward brand-new requirements for talent cultivation in higher education, and how colleges and universities can cultivate new quality talents adapted to the times, the main force lies in the enhancement of practical teaching [5-6].

As an important part of higher vocational education, the practical teaching system is a key link in cultivating talents with innovative consciousness and practical ability, and it is also an important way and core link for vocational colleges and universities to enhance students' vocational ability [7-8]. However, with the rise of new quality productivity, the traditional practice teaching system faces many challenges and opportunities [9]. On the one hand, it tends to focus on the cultivation of basic skills, which is difficult to adapt to the demand for high-quality and innovative talents in the new quality productivity. On the other hand, the rapid development of the new quality productivity provides rich application scenarios and cutting-edge technology for practical teaching, which provides strong support for the innovation of practical teaching system. As a bridge connecting theoretical knowledge and practical application, the innovative practical teaching system creates a "dialogue" with enterprise production through real work scenes, which reduces the difficulty of students' knowledge comprehension and refines students' practical ability in a subtle way, so that they can quickly adapt to the positions in the enterprise [10-11].

New-quality productivity is centered on scientific and technological innovation, which puts forward higher requirements for professional talent cultivation in higher vocational colleges and universities [12]. Hu et al [13] analyzed the driving relationship between new-quality productivity and the development of vocational education and constructed a talent cultivation system based on the fusion of industry and education, which can provide strong support for the development of new-quality productivity by improving the accuracy of talent supply and the quality of cultivation. Liu et al [14] explored the development path of metallurgy education in China based on the current situation and development trend of the metallurgy industry, and they implemented the informationization and service-oriented model, strengthened students' practical ability through school-enterprise cooperation and industry-university-research integration, and cultivated new-quality talents. Yu [15] explored the modernization of the teaching content and the professional integration, the construction and implementation of the diversified teaching mode, and proposed the resource allocation, teaching management, and school-enterprise cooperation mechanism to promote the deep integration of physical education teaching and industry needs, and then cultivate innovative talents that meet the needs of new quality productivity.

At present, the research on the innovative practical teaching mode driven by artificial intelligence technology in the context of industry-teaching integration is also gradually carried out, and this organic integration mechanism effectively solves the problem of disconnection between traditional talent training and industrial demand, and accelerates the development of new quality productivity [16]. Tong et al [17] constructed a practical teaching model integrating industry and education using artificial intelligence technology, and the model can match different teaching methods according to the matching degree of academic performance, practical skills, innovation ability and professional competence, and the practical teaching driven by artificial intelligence has better effect on academic performance and practical skills cultivation. Xu et al [18] developed an innovative vocational digital teaching mode through industry-teaching integration in the context of artificial intelligence, which provides students with a new teaching environment through the information collection and resource equipping of intelligent tools, and the mode cultivates students' vocational competence and improves their participation in teaching and fit with the industry. Yuan et al [19] pointed out that making full use of the favorable conditions and resources in the era of digital economy is conducive to deepening the reform of industry-teaching integration and promoting the two-way connection of supply and demand, and thus cultivating innovative practical talents. Gao et al [20] explored how to integrate advanced intelligent technology into the learning environment, realize enterprise-school resource sharing under the guidance of industry-teaching integration, and correct the deficiencies of the traditional accounting teaching mode with a brand new practical teaching mode, highlighting the students' training in practical skills. It highlights the cultivation of students in practical skills. Wang et al [21] explored the practical education approach of Taishan College of Science and Technology, Shandong University of Science and Technology, China, and found that the integration of industry and education teaching cultivated students' practical ability and operation level, while the personalized and diversified practical teaching system promoted the cultivation of innovative and applied talents.

Although research in the field of industry-teaching integration has a relatively mature theoretical system, the lack of a unified definition due to the scholars' different understandings of industry-teaching integration has led to some differences in the conceptual and practical contents of the theoretical research [22-23]. In addition, although the literature has already explored in depth the policy, mode and implementation process of the integration of industry and education, there are still fewer detailed case studies on how enterprises specifically implement the strategic transformation of the integration of industry and education in the context of the development of the new quality of productivity, especially the lack of research on the dynamic changes and details in the process of the implementation of the strategy. These shortcomings make it difficult for the existing theories to comprehensively guide enterprises to realize effective strategic transformation of industry-education integration in the rapidly developing economic environment.

This paper constructs the evaluation index system of undergraduate innovative practice teaching and new quality productivity, then analyzes the regional differences and spatial evolution of the level of undergraduate innovative practice teaching by using kernel density estimation based on the panel data of 30 provinces (autonomous regions and municipalities) in China from 2014-2024, and adopts the entropy weight method to measure the level of the development of the new quality productivity of each province (autonomous regions and municipalities). Secondly, the impact model of undergraduate innovative practice teaching on new-quality productivity is constructed, data sources are identified, and finally the promotion effect of innovative practice teaching on new-quality productivity is analyzed through benchmark regression and quantile regression.

2. Measurement of the level of innovative practical teaching and new quality productivity in vocational undergraduate programs

2.1. Construction of evaluation index system

2.1.1. Evaluation index system of undergraduate innovative practice teaching level

The construction of undergraduate innovative practice teaching evaluation index system based on the integration of industry and education. The evaluation index system mainly includes practice teaching target system, practice teaching content system, practice teaching support system, and practice teaching effect system as shown in Table 1.

Table 1. Undergraduate innovation practice teaching evaluation index system.

Target layer	Policy Layer
Practical Teaching Objectives	The conformity of practical mathematics standards and training objectives
	The degree of integration between practical teaching standards and job competency standards
Practical teaching content	Practical teaching model content
	Practical teaching level content
Practical teaching support	Construction of practical teaching bases
	Construction of practical teaching platform
Practical teaching effect evaluation	Practical performance evaluation effect
	Effect of student innovation and entrepreneurship

2.1.2. Indicator system for evaluating the level of new quality productivity

New-quality productivity refers to the form of productivity driven by emerging technologies and concepts such as digitization, intelligence and greening, and is the expansion and sublimation of traditional productivity under the leadership of new technologies and new models. Compared with traditional productivity, new quality productivity is significantly different in terms of factors of production, forms of organization and ways of value creation. Traditional productivity mainly relies on factors such as labor, land and capital, emphasizing scale effect and resource consumption, while new quality productivity relies more on new production factors such as knowledge, data and technology, focusing on efficiency improvement and green development. New quality productivity stems from revolutionary breakthroughs in technology, innovative allocation of production factors, and in-depth transformation and upgrading of industries, and its core connotation lies in the fact that laborers, labor objects and means of production have achieved a brand-new leap through the optimal combination, and the significant increase in total factor productivity is an important symbol. Based on the connotation and elements of the new quality productivity, this paper extracts the key points of the new quality productivity, and combines the availability and comparability of data to construct a new quality productivity level measurement index system that includes three dimensions of new quality laborers, new quality labor objects and new quality means of production, as shown in Table 2.

Table 2. Measurement index system of new quality productivity level.

Primary indicator	Secondary indicator
New quality workers (NQW)	Education
	Human capital structure
	Per capita output value
	Income per head
	Employment philosophy
New quality labor object (NQO)	Strategic emerging industries
	Future Industries
	Greens environmental protection
	Pollution discharge
New quality means of production (NQP)	Traditional infrastructure
	Digital infrastructure
	Energy consumption
	Innovation and R&D
	Digital economy
	Enterprise Digitalization

2.2. Research methodology and data sources

2.2.1. Entropy method

In the existing literature, the methods used in the comprehensive evaluation of the indicator system are summarized as subjective assignment method and objective assignment method. The subjective assignment method is mainly to give greater weight to the more important indicators, and determine the ranking of the weight of each attribute according to the knowledge and experience of experts, such as principal component analysis, Delphi method and hierarchical analysis, but the final evaluation results have a certain degree of subjectivity and arbitrariness, and there will be some difficulties in the subsequent analysis; the objective assignment method is to determine the weights based on the degree of connection between the attributes or the magnitude of information provided by each attribute, which is highly objective and easier to analyze subsequently. The objective assignment method is based on the degree of connection of each attribute or the amount of information provided by each attribute, which is objective and easy to analyze. Among them, the entropy method [24] is a comprehensive evaluation method commonly used in the objective assignment method, and this paper adopts the entropy method to comprehensively evaluate the level of development of China's new quality productivity. The data in the above index system come from different levels, in order to eliminate the influence of different scales between the indicators, the data are first standardized, and then the entropy value method is used to assign weights to the indicators, and finally the weights of the indicators are multiplied by the standardized value to arrive at a comprehensive score. The specific steps are as follows:

(1) Data standardization.

$$\text{Positive indicators: } y_{ij} = \frac{x_{ij} - \min\left(x_{ij}\right)}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)}, i = 1, 2, \cdots, m, j = 1, 2, \cdots, n \tag{1}$$

$$\text{Reverse indicators: } y_{ij} = \frac{\max\left(x_{ij}\right) - x_{ij}}{\max\left(x_{ij}\right) - \min\left(x_{ij}\right)}, i = 1, 2, \cdots, m, j = 1, 2, \cdots, n \tag{2}$$

Where x_{ij} denotes the j th indicator value of the i th sample, i denotes the province, j denotes the indicator, and max and min denote the maximum and minimum values of the j th indicator, respectively.

(2) Determine the weights of indicators by entropy value method.

Calculate the weight of the indicator value of the i program under the j indicator:

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{3}$$

When p_{ij} is equal to 0, replace it with 0.000001.

Calculate the entropy value e_j for the j th evaluation indicator:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln\left(p_{ij}\right), k > 0, 0 \bullet e_j \bullet 1 \tag{4}$$

Calculate the weight of the j th evaluation indicator:

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n}\left(1 - e_j\right)}, j = 1, 2, \cdots, n \tag{5}$$

(3) Calculate the composite score.

$$Z_i = \sum_{j=1}^{m} w_j y_{ij}, j = 1, 2, \cdots, m \tag{6}$$

2.2.2. Kernel density estimation

The kernel density estimation method is a non-parametric estimation method, which uses the probability density function fitting from the data itself to obtain a smooth curve, and solves the problem by analyzing the peak of the curve and the ductility and other elements. Its expression is

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{x_i - x}{h}\right) \tag{7}$$

Where: $f(x)$ represents the density function; h represents the bandwidth; x_i is the independently and identically distributed observation of the i th province and region; $K(x)$ represents the kernel function, and in this paper we choose the Gaussian kernel function.

2.2.3. Data sources

In this paper, data representing the development level of digital economy in 30 provinces in China (Tibet, Hong Kong, Macao, and Taiwan are excluded due to serious data missing) from 2014-2024 are selected from the National Bureau of Statistics (NBS), China Social Statistical Yearbook (CSY), China Statistical Yearbook (CSY), and China Statistical Yearbook of Information Industry (CSI) for the relevant years in each province (autonomous region and municipality directly under the central government).

2.3. Empirical results and analysis

2.3.1. Measurement of the level of innovative practice teaching in undergraduate programs

(1) Level of innovative practice teaching

Figure 1 presents the level of undergraduate innovative practice teaching and its changes in the country and the four regions from 2014 to 2024. In the past ten years, the level of undergraduate innovative practice teaching has grown from 0.2741 to 0.5135, which can be divided into five alternating phases of enhancement and decline with the nodes of 2016, 2018, 2020 and 2021, with particularly rapid development after 2021. In terms of level, the eastern region has the highest level of undergraduate innovative practice teaching, except for 2021, all other years are 0.4 and above; except for 2021, the level of undergraduate innovative practice teaching in the northeastern region is higher than 0.3, which is only lower than that of the eastern region, and even exceeds the eastern region to become the region with the highest level of undergraduate innovative practice teaching in 2024; the central region has the lowest level of undergraduate innovative practice teaching, and the level of undergraduate innovative practice teaching in 2014-2024 is the lowest. The level of undergraduate innovative practice teaching in the central region is the lowest, and the average value of the development water from 2014 to 2024 is 0.2671. In terms of the growth rate, the level of undergraduate innovative practice teaching in the eastern, central, western and northeastern regions in 2024 will increase by 4.58%, 11.09%, 34.58%, and 40.22%, respectively, compared with that in 2024.

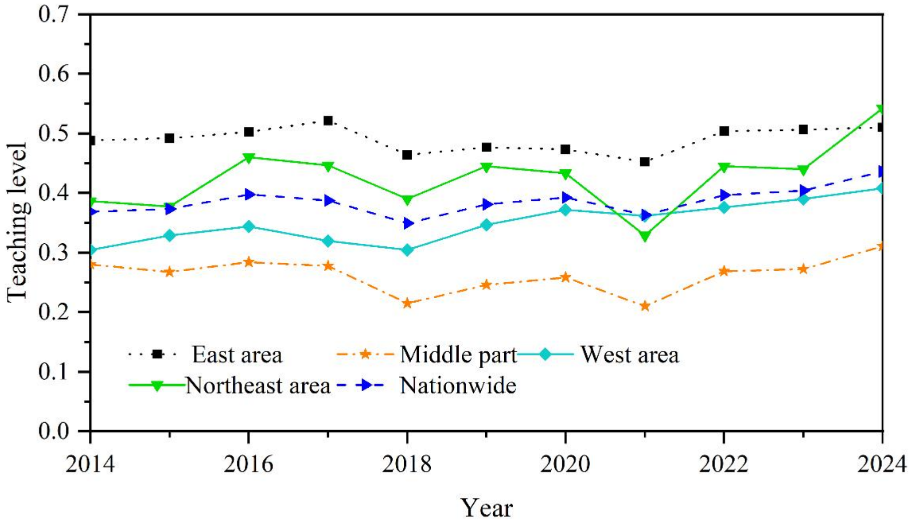


Figure 1. Trends in undergraduate innovation and practice teaching from 2014 to 2024.

(2) Spatial Evolutionary Trends in the Level of Innovative Practical Teaching

1) Regional Comparison in the Central Region

In 2023-2024, the kernel density estimation of the comprehensive index of undergraduate innovative practice teaching level in the central region is shown in Fig. 2, and in general, it is shifted from “long-tailed and short peak” to “short-tailed and peaked”. From the distribution position, the main peak position of the kernel density curve in the region has slightly shifted to the left, indicating that the overall development level of undergraduate innovative practice teaching level in central China has decreased. From the distribution pattern, the wave peak changed from “short and wide” to “high and sharp”, showing a bimodal shape, which means that the regional differences are on a decreasing trend, but there is still the phenomenon of polarization. In terms of the distribution extensibility, there is a right trailing situation, but the extensibility shows an obvious shortening trend, which means that the relative level of undergraduate innovative practice teaching in the central region has declined over time, despite the fact that there are some regions with a high level of undergraduate innovative practice teaching. Analyzing the raw data, it is found that there are six regions in the central region, and the region ranked No. 4 has seen its teaching level drop from the original 64.18 to 51.03; No. 5 has seen its teaching level drop from the original 57.24 to 50.75; and the region ranked No. 6 has seen its teaching level drop from the original 51.90 to 49.86.

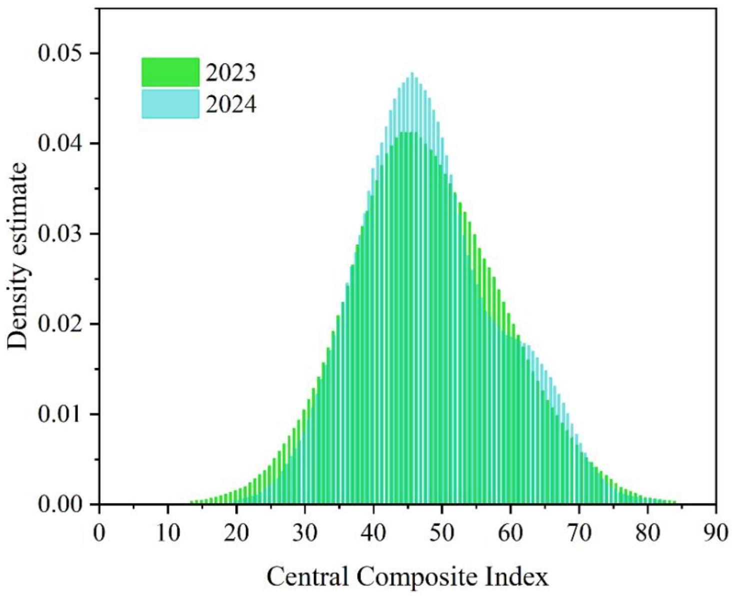


Figure 2. Core density estimation of comprehensive index in central region.

2) Regional Comparison in the Eastern Region

The kernel density estimation of the composite index of undergraduate innovative practice teaching level in the eastern region in 2023-2024 is shown in Figure 3. Overall, the “long tail and short peak” has changed to “short tail and peak”, and from the distribution position, the main peak of the kernel density curve in the region has shifted to the right by a small margin, indicating that the overall development of undergraduate innovative practice teaching level in the eastern region has improved. From the distribution pattern, the wave peak has changed from “short and wide” to “high and sharp”, which means that the difference between districts and counties has been greatly reduced. From the perspective of distribution extensibility, there is a left and right trailing situation, but the extensibility shows an obvious shortening trend, which means that over time, the relative level of undergraduate innovative practice teaching level in the eastern region has increased in the lower counties, and decreased in the higher counties. There are a total of 10 regions in the eastern region, and the 8th ranked region in terms of the level of undergraduate innovative practice teaching and learning has seen its level of teaching and learning rise from 44.89 to 46.11, the 9th ranked region has seen its level of teaching and learning rise from 42.03 to 45.94, and the 10th ranked region has seen its level of teaching and learning rise from 42.11 to 43.86.

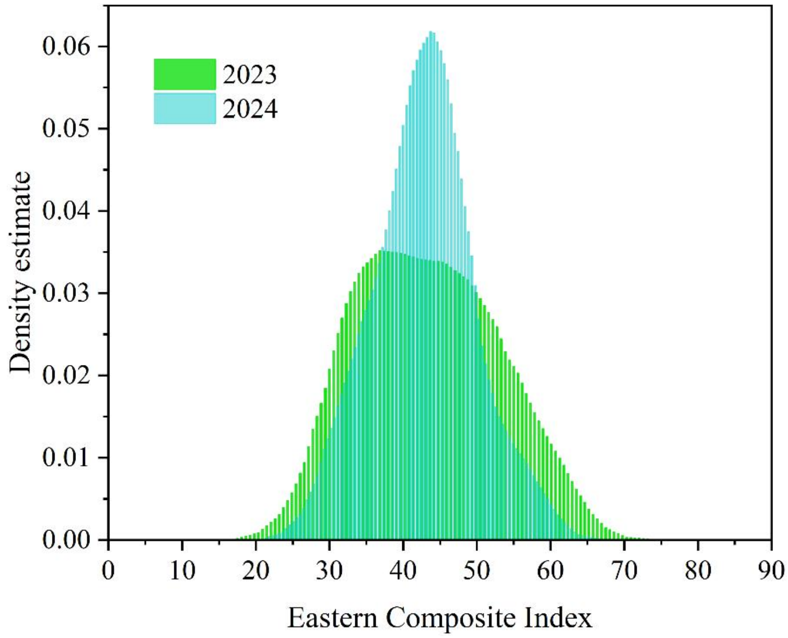


Figure 3. Core density estimation of comprehensive index in east region.

3) Regional Comparison in Western Region

The kernel density estimation of the comprehensive index of undergraduate innovative practice teaching level in the western region in 2023-2024 is shown in Figure 4. Generally speaking, the “short-tailed short peak” has changed to a “tail-less peak”, and from the distribution position, the main peak of the kernel density curve in the region has shifted to the left by a small margin, indicating that the overall teaching level of undergraduate innovative practice in the western region has been lowered. From the distribution pattern, the wave peak changed from “short tip” to “high tip”, which means that the difference between regions is decreasing. From the perspective of distribution ductility, the left trailing to normal distribution pattern means that the relative level of undergraduate innovative practice teaching level in the western region has been improved with the passage of time, and the teaching level in each region is more balanced.

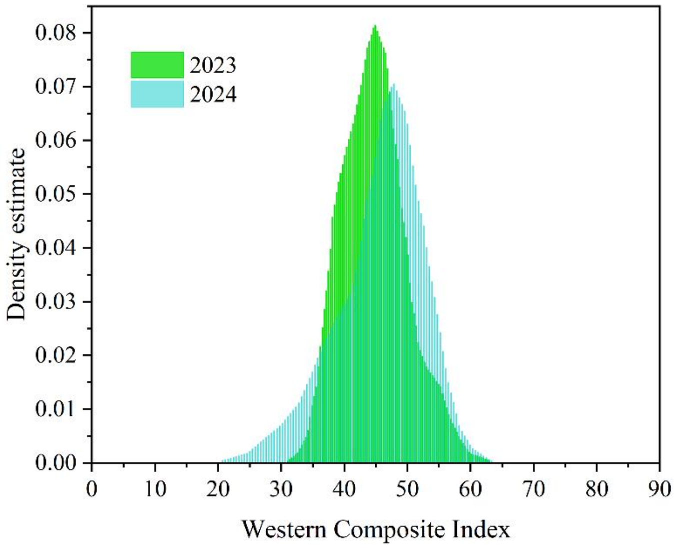


Figure 4. Western composite index kernel density estimation map.

4) Regional Differences in the Northeast Region

In 2023-2024, the kernel density of the composite index of undergraduate innovative practice teaching level in the Northeast region is estimated as shown in Figure 5. From the distribution position, the main peak of the kernel density curve in the region shifted significantly to the right, indicating that the overall teaching level of undergraduate innovative practice in the south has been greatly improved. From the distribution pattern, the wave peak changed from “high and wide” to “short and wide”, indicating that the gap between regions has a tendency to widen. In terms of distribution extension, there is an obvious right trailing phenomenon, but the right trailing is shortened over time, which means that the teaching level of undergraduate innovative practice in the southern region is too high, and the relative development level of the region is lowered.

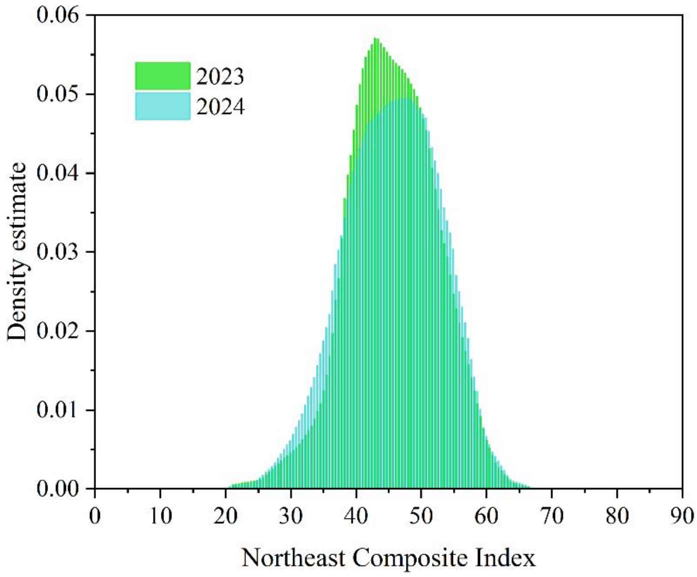


Figure 5. Comprehensive index kernel density estimation map of northeast China.

Overall, from 2023-2024 the differences in the level of undergraduate innovative practice teaching in the region decrease. According to the changes in the overall teaching level and concentration of undergraduate innovative practice teaching, the changes in the development of the regions can be divided into four categories. The first category is characterized by a decrease in the overall teaching level and unchanged concentration, including the western and central regions; the second category is characterized by a decrease in the overall teaching level and a change from a high concentration to a low medium, only the northeastern region; the third category is characterized by a decrease in the overall teaching level and a change from a low concentration to a high medium, only the northern region. It can be seen that a decrease or increase in the overall teaching level of undergraduate innovative practice has little effect on the concentration of teaching level in each region.

2.3.2. Measurement of new quality productivity levels

(1) New quality productivity level

According to the entropy weight method, the annual average value and annual geometric mean growth rate of the index of new quality productivity level in 2021-2024 as shown in Table 3 are calculated to analyze the comprehensive configuration level of the index of new quality productivity level of each province (autonomous region and city) in China.

As can be seen from the table, the annual average value of the new quality productivity index ranked the top 5 provinces (autonomous regions and municipalities) are Guangdong, Jiangsu, Zhejiang, Shandong, Beijing; the annual average value of the ranking of the last 5 provinces (autonomous regions and municipalities) are Gansu, Xinjiang, Hainan, Qinghai, Ningxia; China's new quality productivity index, the highest provinces (autonomous regions and municipalities) is the lowest province (autonomous regions and municipalities) of the 36.16 times; all of the above shows that China (autonomous regions and municipalities) between the new quality productivity index levels between China (regions and cities) is very obvious.

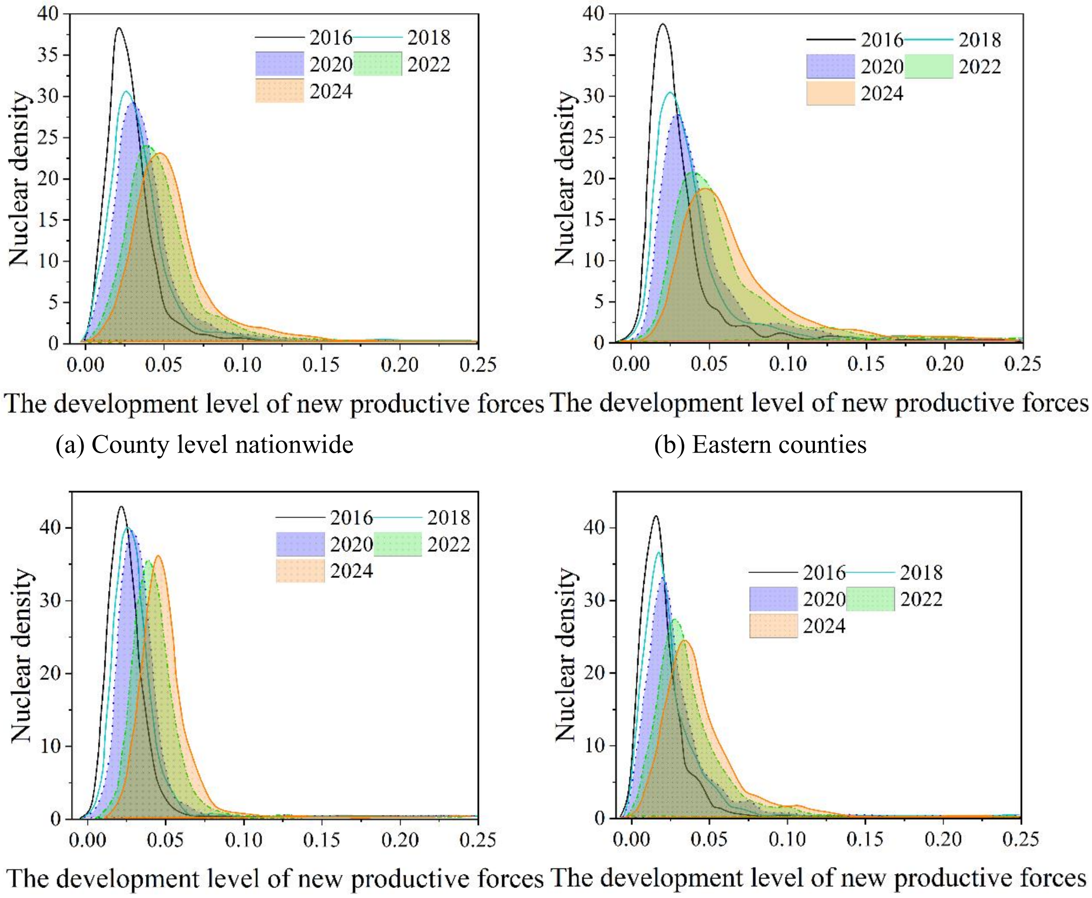
Table 3. Comprehensive Level of the New Quality Productivity Index 2021-2024.

Province	2021	2022	2023	2024	Mean
Beijing	0.0603	0.0512	0.0588	0.0558	0.0565
Tianjin	0.0234	0.0178	0.0198	0.0158	0.0192
Hebei	0.0351	0.034	0.0355	0.0344	0.0347
Shanxi	0.0156	0.0145	0.0152	0.0189	0.0161
Nei Monggol	0.018	0.013	0.0132	0.0123	0.0141
Liaoning	0.0309	0.0212	0.0213	0.0225	0.024
Jilin	0.0176	0.0165	0.0144	0.0137	0.0156
Heilongjiang River	0.0211	0.0175	0.0183	0.0184	0.0188
Shanghai	0.0521	0.0474	0.0499	0.0546	0.051
Jiangsu	0.1136	0.1144	0.1234	0.1108	0.1156
Zhejiang	0.0948	0.0952	0.0966	0.1058	0.0981
Anhui	0.0385	0.048	0.0374	0.0437	0.0419
Fujian	0.0594	0.0503	0.0418	0.0359	0.0469
Jiangxi	0.0254	0.0196	0.0235	0.0219	0.0226
Shandong	0.0732	0.0669	0.0645	0.0632	0.067
Henan	0.0434	0.042	0.0429	0.0411	0.0424
Hubei	0.0359	0.0385	0.0435	0.0397	0.0394
Hunan	0.0373	0.0305	0.0326	0.0307	0.0328
Guangdong	0.1432	0.1476	0.134	0.1439	0.1423
Guangxi	0.0191	0.0157	0.0199	0.0176	0.0181
Hainan	0.0111	0.0064	0.0068	0.0058	0.0076
Chongqing	0.0249	0.0221	0.0192	0.0194	0.0214
Sichuan	0.0393	0.0351	0.0346	0.0359	0.0362
Guizhou	0.0168	0.0132	0.0138	0.0137	0.0144
Yunnan	0.0202	0.0148	0.0155	0.016	0.0166
Shaanxi Province	0.0289	0.0208	0.0235	0.026	0.0248
Gansu	0.015	0.011	0.0109	0.0103	0.0118
Qinghai	0.0076	0.0091	0.0048	0.0051	0.0067
Ningxia	0.0102	0.0047	0.0043	0.0071	0.0066
Xinjiang	0.0127	0.0093	0.0112	0.0100	0.0108

(2) Spatial Evolutionary Trends of Neoplastic Productivity in China

1) Kernel Density Estimation of Neomass Productivity in China

During the observation period, the evolution of county-level new quality productivity development in China and its eastern, central and western regions is shown in Figure 6. The spatial evolution trend of the development level of county new quality productivity in each region shows high similarity, and the center of the density function continues to move to the right over time, indicating that the development level of county new quality productivity in the country as a whole is on an upward trend; meanwhile, the peak value of the wave peak decreases year by year, and the distribution of the width of the wave peak becomes broader, reflecting the widening trend of the gap between the development levels of county new quality productivity in various regions of the country, while the wave peak has widened from “single-peak” in 2007 to “single-peak” in 2007. The wave peak gradually evolved from the “single-peak” pattern in 2007 to the “one main and one small” pattern and the main peak is distributed to the left, and there has been a long right trailing phenomenon and it has become longer in turn, which means that the development level of county new quality productivity has gradually shown the phenomenon of polarization. In addition, the width of the wave peaks of new productivity in the central region has increased less than that in other regions, indicating that compared with the eastern and western counties, the development of new productivity in the central region is more balanced, with the smallest gap in the development of new productivity between counties.



(a) County level nationwide (b) Eastern counties

(c) Central counties (d) Western County

Figure 6. Evolution of China's New Quality Productivity Development Level.

2) Markov chain analysis of new quality productivity development in Chinese counties

Since the development of county new quality productivity has a significant positive spatial correlation during the observation period, the spatial Markov chain can be used to analyze the spatial lag on the convergence evolution of county new quality productivity. In this paper, following the principle of equal spacing method, the 1972 counties in China are divided into four types, namely, low level (L), medium level (ML), medium-high level (MH), and high level (H), with 70%, 100%, and 130% of the average level of the development of new-quality productivity in each year as the cut-off point, and the spatial Markov transfer probability matrices for the level of inclusive financial development in Chinese counties are shown in Table 4. As can be seen from the table, the transfer of new quality productivity development in Chinese counties has the following characteristics: ① The elements on the diagonal are significantly larger than the elements on the non-diagonal, indicating that the club convergence feature is very obvious, and the probability of transfer of the convergence club across the span is generally very low, with a maximum of only 3.84% among all lag types. ② When the spatial lag type is at a low level, the surrounding neighbors have the greatest impact on low and medium-low level counties.

When the spatial lag type belongs to the high level, the club convergence phenomenon is the slightest, the probability of transferring the inclusive financial development of the county to the high level is generally higher, and the probability of the high level county remaining unchanged is the largest 87.62%, indicating that when the county is at a high level its positive spillover effect on the neighboring counties is the most significant, and has a good and significant contribution to alleviating the gap in the development of inclusive financial services between the regions.

Table 4. Space Markov transition probability matrix.

Delayed type	t_i/t_i+1	n	L<70%	70%<ML<100%	100%<MH<130%	H>100%
Low-level neighbor	L<70%	1645	0.9314	0.065	0.0082	0.0028
	70%<ML<100%	1300	0.0971	0.8242	0.0522	0.0341
	100%<MH<130%	921	0.004	0.1331	0.7999	0.0704
	H>100%	888	0.004	0.034	0.0951	0.8742
Low to medium level neighbors	L<70%	586	0.9294	0.0677	0.0042	0.0062
	70%<ML<100%	2414	0.0688	0.8642	0.052	0.0224
	100%<MH<130%	1536	0.0049	0.1333	0.8025	0.0668
	H>100%	1463	0.0095	0.0396	0.1064	0.8519
Medium-high level neighbors	L<70%	1576	0.9188	0.0765	0.0072	0.0049
	70%<ML<100%	1698	0.0729	0.8594	0.0569	0.0182
	100%<MH<130%	1044	0.0049	0.1296	0.8007	0.0722
	H>100%	954	0.0064	0.045	0.1121	0.8439
High-level neighbor	L<70%	1163	0.9035	0.0872	0.0127	0.0041
	70%<ML<100%	1134	0.0927	0.8126	0.0818	0.0203
	100%<MH<130%	890	0.0067	0.1494	0.7579	0.0934
	H>100%	828	0.0042	0.0207	0.1063	0.8762

3. Modeling the impact of innovative practical teaching on new quality productivity in vocational undergraduate programs

3.1. Modeling

According to the previous theoretical analysis, the development of new quality productivity is highly dependent on the deep integration of digital technology and the real economy, which requires workers not only to master traditional professional skills, but also to have new types of abilities such as data thinking, algorithm application and system integration. As a hub connecting industry and education, vocational undergraduate innovation and practice teaching is an irreplaceable and important force to promote the development of new quality productivity. Higher vocational innovation and entrepreneurship education can drive the development of new quality productivity by reshaping the supply system of high-quality innovative talents, empowering the digital and intelligent transformation of industries, fostering the new kinetic energy of green and low-carbon development, and cultivating the innovation culture and entrepreneurship. To this end, the following panel econometric model is constructed to test the overall effect of vocational undergraduate innovation and practice teaching on the promotion of new quality productivity, drawing on previous research literature.

$$NQP_{i,t} = \beta_0 + \beta_1 YJS_{i,t} + \beta_j X_{i,t} + \mu_i + \gamma_1 + \varepsilon_{i,t} \cdot \tag{8}$$

Where: i and t are the province and year of the study, respectively; $NQP_{i,t}$ is an explanatory variable indicating the level of new quality productivity development in region i in year t; and $YJS_{i,t}$ is a core explanatory variable indicating the level of postgraduate education development in region i in year t; $X_{i,t}$ denotes a series of control variables, mainly including the intensity of environmental regulation, the degree of openness to the outside world, the level of urbanization, the level of marketization, and the level of financial development and other five aspects of the variables; μ_i is an individual fixed effect, γ_i is a time fixed effect, and $\varepsilon_{i,t}$ denotes a random error term.

3.2. Selection of variables

3.2.1. Explained variables

The connotation of new quality productivity (NQP) is quite rich, but the definition of its concept has not yet been agreed upon by academics. Starting from the three elements of production proposed by Marx and based on the accessibility of data, this paper draws on the constructed evaluation index system of NQP as shown in 2.1.1, and utilizes the entropy value method to recalculate the comprehensive index of NQP as shown in 2.2.1.

3.2.2. Explanatory variables

The level of innovative practice teaching (PTV) of vocational undergraduate education refers to the type of education at the stage of higher education, which is oriented to vocational needs, based on theoretical knowledge learning and focusing on the cultivation of practical ability, and which cultivates high-quality technical and skilled talents with a certain degree of vocational literacy through systematic specialized courses and practice teaching, as shown in Section II.

3.2.3. Control variables

The study of the mechanism of the level of innovative practical teaching of vocational undergraduates to promote the new quality of productivity included the following variables in the regression model: the intensity of environmental regulation (ER); the degree of openness to the outside world (OPEN); the level of urbanization (Urb); the level of marketization (Market); and the level of financial development (FDL).

3.3. Sample Selection and Data Sources

In this paper, data representing the development level of digital economy in 30 provinces in China (Tibet, Hong Kong, Macao, and Taiwan are excluded due to serious data missing) from 2014-2024 are selected from the National Bureau of Statistics (NBS), China Social Statistical Yearbook (CSY), China Statistical Yearbook (CSY), and China Statistical Yearbook of Information Industry (CSI) for the relevant years in each province (autonomous region and municipality directly under the central government).

4. Analysis of the effect of innovative practical teaching on the promotion of new quality productivity

4.1. Benchmark regression analysis

Regarding the empirical analysis of the impact of undergraduate innovative practice teaching on new quality productivity, this paper intends to explore from the overall scope and divided into regions, as shown in Table 5. Firstly, from the overall scope, the regression coefficient of Education is significantly positive at the 5% level, indicating that the new quality productivity cannot be separated from the promotion of undergraduate innovative practice teaching, and the promotion of undergraduate innovative practice teaching on the new quality productivity is very great, which indicates that the undergraduate innovative practice teaching as a whole has a significant impact on the new quality productivity. However, the pairs of estimates of other control variables are not fully statistically significant, which indicates that undergraduate innovative practice teaching has a relatively close positive relationship with new quality productivity.

Table 5. Benchmark regression results.

Variable	NQP	
	Model(1)	Model(2)
PTV	0.0077*** (2.87)	0.0077*** (2.65)
ER	0.0041 (1.07)	0.0041 (0.91)
OPEN	-0.0023 (-1.38)	-0.0023 (-1.45)
Urb	0.0079 (0.43)	0.0079 (0.41)
Market	0.0374*** (2.81)	0.0374 (1.69)
FDL	0.0429*** (2.95)	0.0429 (1.28)

Note: Values in parentheses indicate t-test values of regression coefficients: ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively. Model (1) refers to the results using OLS regression, and model (2) refers to the results using OLS regression (robustness analysis).

In order to explore the specific impact effect of undergraduate innovative practice teaching on each dimension of rural revitalization, regression analysis was conducted on each dimension of rural revitalization, and the regression results are shown in Table 6. In the aspect of industrial prosperity, the regression coefficient of undergraduate innovative practice teaching on industrial prosperity is 0.0054, and the regression coefficient is larger, indicating that undergraduate innovative practice teaching has a larger effect on the promotion of new-quality productivity, i.e., undergraduate innovative practice teaching can have a significant effect on new-quality productivity. This is in the aspect of new quality laborers, the regression coefficient of undergraduate innovation practice teaching on laborers is 0.0091, and it is significantly positive at 10% level, indicating that undergraduate innovation practice teaching can significantly promote new quality laborers. In terms of new quality labor objects, the regression coefficient of undergraduate innovation practice teaching on new quality labor objects is 0.0116, and it is significantly positive at 10% level, indicating that undergraduate innovation practice teaching can significantly promote new quality labor objects. The development of undergraduate innovative practice teaching effectively drives economic development, reduces energy consumption, and then promotes the improvement of the overall level of integration of industry and education.

Table 6. Regression analysis of new quality productivity on various dimensions.

variable	NQP	NQW	NQO	NQP
PTV	0.0054* (0.14)	0.0091** (1.79)	0.0116*** (2.79)	0.191*** (4.53)
ER	0.0014 (0.036)	0.0111 (1.58)	0.009 (0.14)	0.0087 (2.25)
OPEN	-0.0017 (-0.84)	-0.0017 (-0.54)	-0.0054* (-1.96)	-0.0067** (-2.17)
Urb	0.0148 (0.94)	-0.0095 (-0.37)	0.0837*** (3.57)	0.0994*** (3.86)
Market	0.0147 (0.94)	-0.0095 (-0.37)	0.0833*** (3.56)	0.0992*** (3.62)
FDL	0.0147 (0.86)	-0.0443 (1.57)	0.0297 (1.18)	0.0447 (1.62)

Note: Values in parentheses indicate t-test values of regression coefficients: ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

4.2. Quantile regression analysis

4.2.1. Quantile regression principle

Quantile regression is one of the methods of regression analysis,in order to find an optimal regression estimate that best represents all the observations to represent the relationship between the dependent and independent variables, it emphasizes the change of conditional quantiles, can specify different locations of the distribution, and can provide a more comprehensive understanding of how the distribution of the dependent variable is affected by the respective variables. Compared with the traditional regression analysis that only obtains the central tendency of the dependent variable, quantile regression can further infer the conditional probability distribution of the dependent variable [25]. The specific procedure is as follows:

Suppose Y is a continuous random variable with distribution function $F(y), Y$ at quantile y_τ, defined as:

$$F\left(y_\tau\right) = P\left(Y \leq y_\tau\right) \tag{9}$$

The quantile y_τ divides the totality into two parts less than or equal to y_τ and greater than y_τ, and the probabilities of each of the two parts are τ and $1-\tau$ respectively, and if τ is exactly equal to 0.5, then it indicates the median, which is located at the center and divides the whole into two parts equally. If the quantile regression model equation is:

$$y_i = \beta(\tau)x_i^T + \varepsilon(\tau) \tag{10}$$

The quantile corresponding to the parameter vector β can be minimized by for the regression model as:

4.2.2. Quantile regression advantages

Quantile regression has the following advantages:

(1) This regression is able to fit the full distributional information of the data, and it can also analyze how the explanatory variables affect the median, quartiles, etc. of the explanatory variables. Estimates of regression coefficients under different quartiles are often different, i.e., the explanatory variables have different impacts on different levels of the explained variables.

(2) Quantile regression does not require the error term to be "normally distributed". Therefore, quantile regression coefficient estimates are more robust than non-normal distributions.

4.2.3. Quantile regression analysis of effects on neoplasm productivity

In order to further analyze the impact of rural education on rural revitalization, the conditional quantile of the explanatory variables is considered to analyze the trend and marginal effect of the explanatory variables on the explanatory variables at different categorization levels. The quantile regression model is established to examine Q10, Q25, Q50, Q75, and Q90 as the quantile points. The regression results are shown in Table 7.

As can be seen from the table, overall the development of undergraduate innovative practice teaching can significantly contribute to the implementation of new quality productivity, and the two show a significant positive effect, and the effect changes in a U-shape. Specifically, at the 10% quantile each level of rural education will increase the level of new quality productivity by 0.0036 units to the 50% quantile each unit of rural education will increase the level of new quality productivity by 0.0022 units to the 90% quantile each level of undergraduate innovation and practice teaching will increase the level of new quality productivity by 0.0081 units, it can be seen that The change trend of the promotion effect of undergraduate innovative practice teaching on the new quality productivity is first decreasing and then increasing, from significant to insignificant to significant U-shaped change, at the end point, the promotion effect of undergraduate innovative practice teaching on the new quality productivity is most obvious.

Table 7. Quantile regression results.

	Q10	Q25	Q50	Q75	Q90
NQP	0.0039** (2.97)	0.0042* (1.92)	0.0022 (0.99)	0.0085*** (2.78)	0.0081** (2.35)
NQW	0.0002 (0.26)	0.0002 (0.01)	0.0001 (0.07)	-0.0085 (-1.56)	0.0032 (0.42)
NQO	0.0221 (1.37)	0.0252* (2.18)	0.0000 (0.00)	-0.0001 (-0.01)	-0.0012 (-1.09)
NQP	0.0017 (1.43)	0.0038 (1.09)	0.0115 (1.99)	0.0162*** (2.93)	0.0186** (1.94)

5. Conclusion

This paper constructs evaluation indexes of undergraduate innovative practice teaching level and new quality productivity based on panel data of 30 provinces in China from 2014 to 2024. The entropy weight method is used to calculate the level of new quality productivity in each province, and then the kernel density estimation is further used to analyze the regional differences and spatial evolution of undergraduate innovative practice teaching level and new quality productivity at the national level, in the four regions and in each province. Finally, the regression model is used to analyze the impact of undergraduate innovative practice teaching level on new quality productivity and its dimensions:

(1) The development of undergraduate innovative practice teaching level is still insufficient, and the level is generally low, but shows an upward trend, with regional differences. The level of undergraduate innovative practice teaching is higher in the eastern and northeastern regions, the western region is catching up rapidly, and the level of undergraduate innovative practice teaching is the lowest in the central region.

(2) The differences in teaching level of innovative practice among regions and counties in the region are reduced, the decrease or increase of the overall teaching level has little effect on the concentration of teaching level in each region and county, and the level of teaching of innovative practice is positively proportional to the extreme difference, i.e., the higher the level of teaching is, the bigger the extreme difference is, and the decrease in the level of teaching is, the lesser the extreme difference is.

(3) The gap in the level of new quality productivity index between China (districts and cities) is obvious, and the central counties are more balanced compared to the eastern and western counties, and the gap in the development of new quality productivity between counties is the smallest.

(4) The regression coefficient of undergraduate innovative practice teaching on new quality productivity is significantly positive at the 5% level, indicating that undergraduate innovative practice teaching as a whole has a significant effect on new quality productivity. Under quantile regression, the promotion effect of undergraduate innovative practice teaching level on new quality productivity shows U-shaped change.

Funding

This research was supported by the Achievements of Philosophy and Social Sciences Planning Project in Hangzhou City; Funding from the Key Research Base of Philosophy and Social Sciences in Hangzhou, 'Modern Vocational Education Research Center' Base Project; 2023JD49; Research on the Implementation of the Symbiosis Mechanism of Industry Education Integration in Vocational Colleges.

References

1. Dai, D., & Zheng, Y. (2025). The New Quality Productive Force, Science and Technology Innovation, and Optimization of Industrial Structure. Sustainability, 17(10), 4439.
2. Liu, Z. (2024). New Production Relations Driven by New Quality Productive Forces: Trends, Challenges and Countermeasures. China Finance and Economic Review, 13(4), 45-58.
3. Gong, X. (2024). Performance evaluation of industry-education integration in higher education from the perspective of coupling coordination-an empirical study based on Chongqing. PloS one, 19(9), e0308572.
4. Liang, S. Z., Xu, J. L., Hsu, Y. M., & Liu, Y. Q. (2025). Bridging the Gap: An Analysis of Key Factors Driving Industry-Education Integration in Application-Oriented Undergraduate Institutions. Current Science, 5(4), 3504-3514.
5. Liang, H., & Huang, W. (2025). Technological Innovation Spurring New Quality Productive Forces and Its Global Effect. China Finance and Economic Review, 14(1), 50-69.
6. Chen, X., Liu, L., Li, D., Han, Y., & Liu, X. (2025). The impact of artificial intelligence on the new quality productive forces of enterprises. Journal of Digital Management, 1(1), 1-13.
7. Chen, S. (2017). Higher education development path based on practical education pattern. Eurasia Journal of Mathematics, Science and Technology Education, 13(12), 7921-7927.
8. Xinming, Z. (2023). Research on cultivating innovation and practical skills in higher vocational education. Frontiers in Educational Research, 6(26), 29-36.
9. Wu, F. (2024). Practical Exploration of Computer Teaching Mode in Higher Vocational Education from the Perspective of Industry Education Integration. Frontiers in Educational Research, 7(4).
10. Yang, C., Huan, S., & Yang, Y. (2020). A practical teaching mode for colleges supported by artificial intelligence. International Journal of Emerging Technologies in Learning (IJET), 15(17), 195-206.
11. Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. British journal of educational technology, 53(4), 914-931.
12. Zhang, C. (2024). and Entrepreneurship Personnel Training Driven by New Quality Productive Forces. Advances in Artificial Systems for Logistics Engineering IV, 223, 417.

13. Hu, K., & Li, X. (2024). Research on industry-education integration and talents cultivation of vocational education empowering new quality productive forces. J High Vocat Educ, 1, 211-8.
14. Liu, Y., Wang, C., & Chen, Z. (2024). Cultivation of Highly Skilled Talents at the Bachelor degree of Vocational Education in Major Iron and Steel Metallurgy--Exploration Under the Background of New-Quality Productive Forces From the Perspective of Industry-Education Integration and School. International Journal of Educational Teaching and Research, 1(3).
15. Yu, B. (2024). Reform of Physical Education in Vocational Colleges under the Context of New Productive Forces. Journal of Modern Business and Economics, 1(2).
16. Li, X. (2024). Development path of low-altitude logistics and construction of industry-education integration community from the perspective of new quality productive forces. Industry Science and Engineering, 1(10), 44-51.
17. Tong, L., Zhang, J., Yue, L., Chen, L., & Wang, M. (2025). A neural network-based model for cultivating applied talents in the context of industry-education integration. Discover Artificial Intelligence, 5(1), 1-14.
18. Xu, J., & Zhang, J. (2025). Exploration on the Innovative Development Model of Digital Teaching Materials in Higher Vocational Colleges in China Under the Background of Industry-education Integration: Taking Digital English Teaching Materials in Higher Vocational Medical Colleges as an Example. The Educational Review, USA, 9(7).
19. Yuan, P., & Yang, X. (2024). Exploration of the model of deepen industry–education integration in the digital economy era. Journal of Internet and Digital Economics, 4(3), 179-186.
20. Gao, J., & Singh, C. K. S. (2025). Research on the Optimization Pathways of Practical Teaching Models for Vocational College Accounting Teachers Under the Guidance of Industry-Education Integration. Journal of Integrative Education Studies, 1(2), 7-12.
21. Wang, H., Yu, L., Geng, X., & Meng, C. (2019, June). Construction of practical education system for innovative applied talents cultivation under the industry-education integration. In Proceedings of the 5th International Conference on Frontiers of Educational Technologies (pp. 68-72).
22. Wang, Y. (2025). Industry-Education Integration: Modeling Dilemmas and Practical Tensions. Frontiers in Economics and Management, 6(10), 92-99.
23. Zhao, W. (2024). Innovation and practice of talent cultivation models in higher education from the perspective of industry-education integration. Higher Education Practice, 10, h241515.
24. Xianying Cao & Minhua Sun. (2025). Investigation of the modulation of the microstructure in CuZr alloys by the addition of Zr using the atomic entropy method. Applied Physics A,131(11),856-856.https://doi.org/10.1007/S00339-025-08982-1.
25. Maleshoane Teleki,Makoala V. Marake,Botle E. Mapeshoane,Molutsoane Motšoane,Mantsatsi Moleleki,Kotelo Nkunyane... & Mashekoe Liemo Likoti. (2025). Spatial Distribution of Soil Organic Carbon Along a Toposequence Using Quantile Regression Forest in Lesotho. Applied and Environmental Soil Science,2025(1),2342355-2342355.https://doi.org/10.1155/AESS/2342355.