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Construction of implementation system for vocational education targeted training model based on BP neural network under the integration of industry and education

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Abstract: Industry-education integration has become a pivotal national strategy in China, yet its complex interactions are difficult to capture with traditional models, which often rely on empirical methods lacking precision. To address this gap, this study introduces a BP neural network-based evaluation approach. By iteratively adjusting neuron weights to fit nonlinear functions, the method enables accurate assessment of industry-education integration. The research highlights the importance of vocational education, identifies key challenges, and explores its role in China's educational system. A neural network model is built using 10 secondary indicators, with simulation and validation performed in MATLAB on real-world data. Results show strong dynamic tracking and fitting accuracy, providing a scientific basis for precise evaluation. This study contributes an innovative data-driven method for optimising vocational training models and offers valuable insights for policy development and system improvement.

Keywords: industry-education integration; BP neural network; vocational education; oriented training; system construction.

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1 Introduction

The talent cultivation model in vocational education is closely tied to the quality and competency levels of trained individuals. With an increasing focus on vocational education and skilled talent development, many institutions are striving to establish effective training models tailored to the needs of vocational education (Fang, 2024). Oriented vocational education, which aligns educational content with market demands, enhances the relevance and practicality of education, ultimately improving its overall quality (Wang et al., 2023). This model provides students with clear career pathways, enabling them to achieve better employment outcomes (Long and Wang, 2024). Moreover, it ensures that professionals are equipped to meet specific job requirements, thereby supporting societal and economic development (Wang, 2023). However, the operational framework of this model in vocational education remains unclear and lacks innovative approaches (Gui and Lin, 2024).

In response to these challenges, industry-education integration has emerged as a critical strategy to bridge the gap between educational content and job market demands (Chen et al., 2023). This approach fosters collaboration between vocational institutions and enterprises, ensuring the relevance of education and enhancing students' employability (Zhang and Weng, 2024). Through such partnerships, vocational institutions and enterprises can jointly engage in research projects, facilitating the transformation of theoretical research into practical applications and driving technological innovation (He et al., 2023). This collaboration promotes regional economic development while enabling institutions to better align their programs with societal needs (Ma and Ding, 2022). Additionally, industry-education integration provides real-time feedback on job market requirements, empowering vocational institutions to adjust their curriculum and professional programs accordingly (Hao et al., 2024). Consequently, exploring the construction of industry-education integration communities is essential for advancing vocational education reform and improving education quality (Deng et al., 2024).

Existing research on industry-education integration, both domestically and internationally, covers a broad spectrum of topics, including model classification, community mechanisms, influencing factors, and evaluation systems. For instance, Lemos categorised industry-education integration models into bidirectional, commercial, service-oriented, and traditional types based on the interactions between entities (Ali and Johl, 2022). White et al. suggested selecting different models depending on the development stage of an enterprise, such as adopting joint production during the invention stage and directive models during the technology differentiation stage (Yang, 2024). Nanzu Muhai proposed three types of models – educational, employment-oriented, and research-based – tailored to specific objectives (Wang et al., 2022). Additionally, scholars like Polidoro advocate establishing systems of credit, management, and constraints to enhance community mechanisms (Yujie et al., 2022). Other studies suggest the use of incentive mechanisms to improve collaboration between universities and enterprises (Burhanuddin, 2024). Dennis et al. emphasised the importance of a comprehensive working system to promote effective school-enterprise integration (Qin and Liu, 2021).

Despite these contributions, existing studies face notable limitations. Many lack theoretical depth and often focus narrowly on the roles of governments, schools, and enterprises, neglecting the perspectives of students and societal stakeholders (Hu et al., 2024). Furthermore, research perspectives remain largely confined to pedagogy and economics, with insufficient attention to broader issues such as stakeholder interests and their dynamics (Tusquellas et al., 2024). Evaluation systems have been developed to assess the effectiveness of integration models. For example, Kaklauskas introduced a sustainable development evaluation framework, while Gibson proposed a hierarchical evaluation system (Kuang et al., 2020). Nevertheless, these models require refinement to fully address the complexities of industry-education collaboration (Chen, 2023).

To overcome these challenges, this study introduces a BP neural network-based evaluation model aimed at optimising vocational education training within the framework of industry-education integration (Zhang and Weng, 2024). The BP neural network enables precise evaluation by simulating the mapping and feedback mechanisms of neuron weights, facilitating the fitting of complex nonlinear functions (Baldigara and Duvnjak, 2021). Constructed with 10 secondary indicators, the BP neural network model has been validated through MATLAB simulations, which demonstrate its superior performance in dynamic tracking and fitting accuracy (Wang et al., 2022). This innovative approach provides both theoretical and practical insights into the integration of education and industry while offering a robust tool for evaluating vocational education models (Li et al., 2021). By enhancing collaboration between educational institutions and enterprises and aligning educational content with industry needs, the model significantly improves vocational education outcomes (Chen et al., 2023).

The ongoing development of artificial intelligence (AI) and deep learning technologies offers further potential for advancing industry-education integration. For example, deep learning algorithms, such as deep belief networks and convolutional neural networks, can enhance speech recognition accuracy, further optimising integration models (Huang and Zheng, 2023). By comparing the performance of various deep learning algorithms, researchers can identify more effective models for industry-education integration (Wang et al., 2023). As industry-education integration continues to evolve, future research must focus on refining these models to meet the dynamic demands of society and industry (Baldigara and Duvnjak, 2021).

2 Materials and methods

2.1 Core concepts and fundamental theories of industry-education integration in vocational education

The core concept of industry-education integration in vocational education lies in the close connection between the industrial system and the vocational education system, achieved through resource sharing, complementary advantages, and mutual benefits. This integration seeks to establish a cohesive ecosystem that aligns the education chain, talent chain, industrial chain, and innovation chain. By fostering collaboration between education, industry, and technology, it aims to achieve symbiotic goals such as talent cultivation, industrial revitalisation, and innovative development. Industry-education integration is not merely a functional tool or method but an essential attribute, representing a novel ecosystem formed by the interaction of various systems. It emphasises the merging of different system components while preserving their relative independence, enabling the creation of new functions that the original systems alone could not achieve. Through this process, integration produces emergent properties that drive system-level innovation and development.

The theoretical framework supporting industry-education integration encompasses multiple perspectives. Human resource development theory provides a goal-oriented foundation, emphasising the pursuit of value through the integration of education and industry in vocational education. By connecting the education, talent, industrial, and innovation chains, this approach establishes a talent ecosystem centred on the flow of knowledge and skills. The integration fosters system-level connections, where resource-sharing and collaboration facilitate the emergence of new synergies. The theory of human assumptions underpins the value selection process of industry-education integration. At its core, this process examines human nature in the context of trade-offs and value judgements, reflecting the 'human' dimension of industry-education integration. It highlights how stakeholders engage in value-driven decision-making, navigating priorities and compromises to achieve shared goals.

Stakeholder theory explains the collective action dynamics inherent in industry-education integration. This theory emphasises the importance of aligning the interests of all involved parties – industry, education, and society – by identifying stakeholders and their respective value pursuits. Through collaboration, the integration process seeks to find common ground that benefits all participants while addressing their individual needs.

Finally, the triple helix model theory captures the structured action process of industry-education integration, focusing on the relationships among schools, enterprises, and government. This model underscores the diverse and interconnected nature of the integration system, which comprises multiple entities, including research institutions, industry associations, and social organisations. Each entity occupies a specific ecological niche, contributing its unique resources and functions to the system. These interdependencies form a structured and dynamic ecosystem that supports the continuous evolution of industry-education integration.

By synthesising these theoretical frameworks, industry-education integration in vocational education emerges as a dynamic and adaptive process that balances independence with collaboration. It fosters mutual benefits for all stakeholders while creating new opportunities for talent cultivation, industrial innovation, and societal advancement.

2.2 The component boundaries of industry-education integration in vocational education

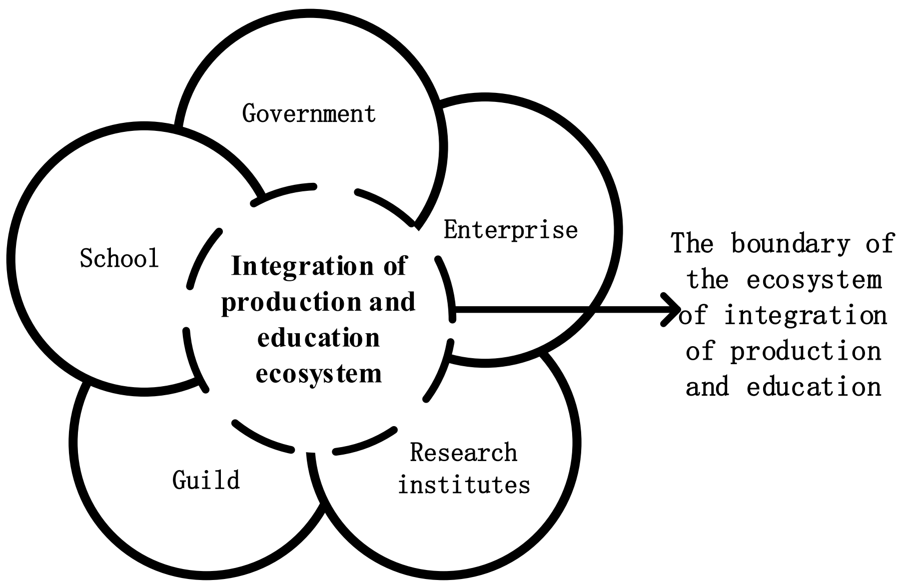
The industry-education integration ecosystem in vocational education has a distinct structure, comprising spatial, quantitative, nutritional, and functional dimensions, which collectively ensure the system's steady state, dynamic balance, and sustainable development. The primary functions of this ecosystem include talent cultivation and the innovative advancement of industrial revitalisation. As an artificial ecosystem, its construction and the configuration of its environmental components are shaped by human intentions. This system is characterised by a high degree of openness and hierarchy.

The industry-education integration ecosystem in vocational education consists of core components and environmental components. Both components exhibit specific characteristics: the core components are diverse, hierarchical, and relative, with variations depending on different perspectives and levels. The environmental components encompass all elements outside the core components, with ecological factors being the most critical. These ecological factors positively influence the core of the ecosystem and can be categorised as primary factors, dominant factors, key factors, or 'residual' factors, depending on their mode of action and impact.

The boundaries of the industry-education integration ecosystem in vocational education serve as demarcations that distinguish different entities. These boundaries are not physical; instead, they are invisible, vague, and subject to dynamic change. They represent a crucial attribute of the system, playing an essential role in maintaining its independence, isolating and differentiating various systems, and fostering system diversity.

Within the functional framework of industry-education integration, system integration is a means rather than an end. It represents partial rather than complete integration, as each subsystem – such as schools, government, and enterprises – retains its independence within its respective boundaries. These boundaries ensure that each entity operates autonomously while contributing to the ecosystem's overall function. The boundary schematic of the industry-education integration ecosystem is illustrated in Figure 1.

Figure 1 Schematic diagram of the boundaries of the industry-education integration ecosystem



2.3 Current status and cause analysis of industry-education integration in china's vocational education

China's vocational education industry-education integration faces a series of challenges that necessitate comprehensive improvements across multiple levels. These include policy design, coordination among implementing agencies, enterprise incentive mechanisms, the enhancement of implementers' quality, the active participation of target groups, and the optimisation of environmental factors, all aimed at maximising policy effectiveness.

The three primary entities – enterprises, government, and schools – often experience value conflicts in the process of industry-education integration due to differing interests. Enterprises primarily focus on economic benefits, the government prioritises regional economic and educational development, while schools aim to cultivate high-quality technical and skilled personnel. These divergent objectives create challenges in defining the role and status of enterprises, ultimately impacting the effectiveness of policy implementation.

The execution of industry-education integration policies involves multiple government departments, such as the Ministry of Education, the Ministry of Finance, the Ministry of Human Resources and Social Security, and the National Development and Reform Commission. Overlapping functions among these departments create significant barriers to effective communication and coordination. Furthermore, poor communication between the central and local governments exacerbates the issue, as local governments often exercise discretionary power in implementing central policies, potentially leading to deviations from intended policy objectives.

An inadequate enterprise incentive mechanism and an underdeveloped school-enterprise cooperation framework are major factors contributing to the insufficient motivation of enterprises to participate in industry-education integration. There is often a mismatch between the skilled talent needs of enterprises and the talent cultivated by schools. Moreover, enterprises face the risk that the talents they help cultivate may not remain within their organisations, leading to a dual loss of costs and benefits. This further dampens enterprises' enthusiasm for engaging in industry-education integration.

The quality of policy implementers also plays a crucial role in the success of industry-education integration. Currently, many implementers lack adequate recognition and understanding of industry-education integration policies. Additionally, their professional skills and knowledge reserves are insufficient, making it difficult for them to meet the complex demands of policy execution effectively. These gaps in implementer competence hinder the realisation of policy objectives and undermine the overall impact of industry-education integration initiatives.

3 Result

3.1 Construction of an ecological system for targeted talent cultivation in vocational education under industry-education integration

As the employment market continues to evolve, enterprises increasingly face challenges related to talent structure conflicts and employee retraining, emphasising the necessity for the co-evolution of school education and industrial development. From a practical standpoint, industry-education integration has emerged as a crucial strategy for China to pursue high-quality development in response to the demands of changing times. It represents an integrative social engineering approach that encompasses multiple subsystems, including higher education, industrial development, technological planning, and political governance.

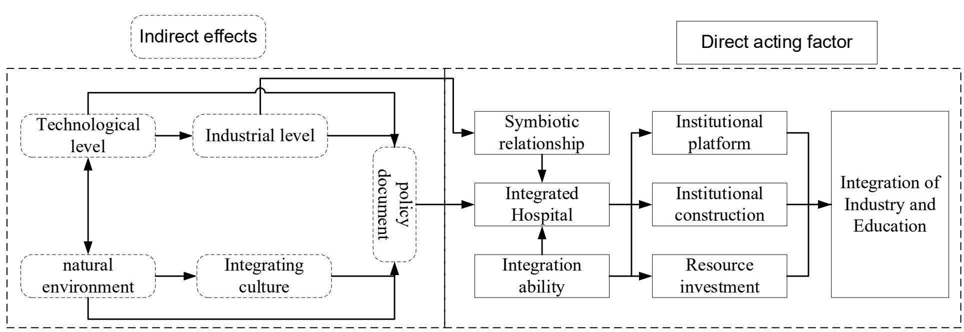
On the one hand, the rapid advancement of technology has facilitated the swift integration of social divisions of labour, particularly through innovations such as the Internet of Things and blockchain. These new technologies increasingly intertwine human lives with technology, profoundly reshaping educational and cultural forms. This is objectively reflected in the growing demand for the integrated development of multiple disciplines. On the other hand, the modern industrial economy is undergoing a transition from capital-intensive models to an era of intelligence, characterised by a reduced need for simple labour and an increased demand for integrated technical talent.

The successful implementation of industry-education integration requires the active participation of key stakeholders, including schools, enterprises, government authorities, and industry associations. Historically, the ancient apprenticeship system in China serves as an early example of 'vocational education,' where students lived and worked alongside their teachers, learning skills in real work environments. This system effectively ensured that students developed both practical skills and vocational ethics. However, after the Industrial Revolution, vocational schools became increasingly detached from specific jobs and production processes, resulting in gaps in students' foundational vocational ethics, qualities, and career planning. This detachment was, in part, a response to the growing knowledge requirements for skills in the post-Industrial Revolution era.

As industrial development continues to evolve, this separation between education and industry has led to persistent challenges, such as 'learning without application' and 'applying without research'. Graduates often fail to meet the skills and knowledge demands of employers, necessitating costly retraining by companies. Similarly, enterprises face difficulties in recruiting research and technical personnel with practical experience on the front lines, hindering their ability to effectively address real-world engineering challenges.

The development of industry-education integration must align with the general evolutionary principles of system development, involving deliberate design and process regulation to gradually enrich its structure and content. Since the issuance of relevant policies on industry-education integration by the State Council in 2017, scholars both domestically and internationally have engaged in extensive discussions and studies. These studies focus on factors related to key entities such as schools and government, as well as objective elements like systems, culture, and practices. These factors are categorised into various ecological components that interact and influence one another, making system evaluation and accurate modelling particularly challenging (Figure 2).

Figure 2 Dynamic interactions among multiple ecological factors in industry-education integration



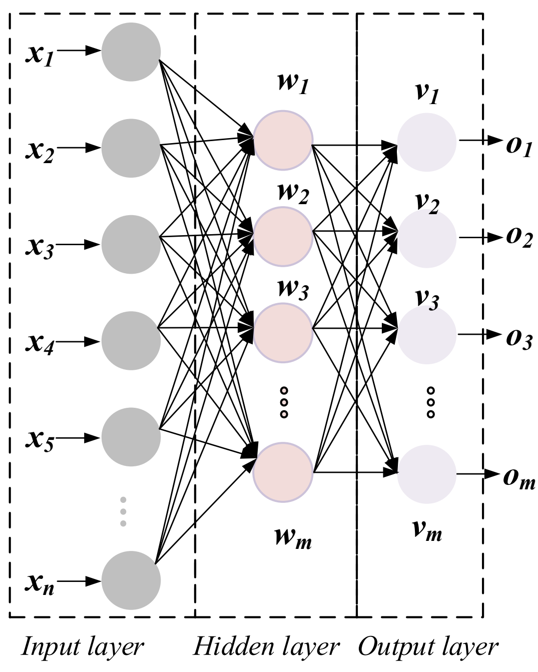
Consequently, much of the research on industry-education integration has relied on empirical criteria, which often lack precision. The dynamic coupling between different ecological factors is difficult to quantify through modelling, leaving policy formulation and adjustments heavily reliant on statistical data. This reliance underscores the need for more advanced methods to evaluate and optimise the complex interactions within the system, ensuring that industry-education integration continues to evolve in alignment with societal and industrial needs.

3.2 BP neural network model and theory

Simulating the human brain for data analysis and processing has been a long-standing research objective for scientists. This has led to the development of artificial neural network (ANN) technology, which mimics the structure of human brain neurons and possesses learning capabilities. Over time, ANN technology has matured significantly.

In the 1980s, David Rumelhart and David Parker introduced the backpropagation (BP) algorithm, building on the foundations of the single-layer perceptron (M-P model). The BP algorithm uses the squared network error as the objective function and applies gradient descent to optimise it, resulting in a nonlinear optimisation method for minimising errors. Through this process, the BP neural network corrects errors and adjusts network weights in real-time by transmitting data through the input layer, hidden layer, and output layer. This adjustment occurs via a combination of forward propagation and backpropagation.

Figure 3 Classic hierarchical block diagram of BP neural network (see online version for colours)



The BP neural network's ability to iteratively adjust weights allows it to simulate the mapping relationships of highly complex nonlinear functions. This makes it particularly effective for analysing multidimensional and high-order mathematical relationships, especially in scenarios where precise mathematical models are challenging to establish. The flexibility and adaptability of the BP neural network have made it a powerful tool for tackling problems involving complex data structures and dynamic relationships, as illustrated in Figure 3.

3.3 Industry-education integration evaluation system based on BP neural network

The implementation training model for industry-education integration should be dynamically adjusted based on existing implementation outcomes. To support this, this paper establishes an evaluation system for industry-education integration utilising BP neural networks, serving as a critical foundation for optimising the implementation process.

First, a comprehensive indicator system is constructed, comprising four primary indicators: the key entities of industry-education integration, the social environment, the practical processes, and the outcomes. To further refine the system, three secondary indicators are included under the 'entities' category: schools, enterprises, and other relevant stakeholders. For the 'environment' category, two secondary indicators are added, focusing on institutional and resource environments. The 'process' category incorporates two secondary indicators addressing integration frequency and intensity. Lastly, the 'outcomes' category includes three secondary indicators: school training outcomes, enterprise employment outcomes, and talent development outcomes.

In this framework, 10 secondary indicators are selected as the output layer of the BP neural network, with the output layer representing the integration evaluation score. The hidden layer is designed to effectively capture the relationships between these indicators and the evaluation score, which can be mathematically expressed as follows:

$$h = \frac{i + o}{1 + e} \tag{1}$$

Here, i represents the number of input layers, o represents the number of output layers, and e is the natural constant. In this case, h is set to 4.

To validate the effectiveness of the proposed BP neural network model, evaluation data from an experimental class focused on industry integration training at a certain vocational higher education institution over the past five years was selected. To avoid errors caused by differences in the magnitude of data between various indicators, this study employed the Min-Max Scaling method for normalisation:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

In the formula, X_{norm} represents the normalised value, while $X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the dataset, respectively. Here, the data can be mapped to the interval [–1, 1].

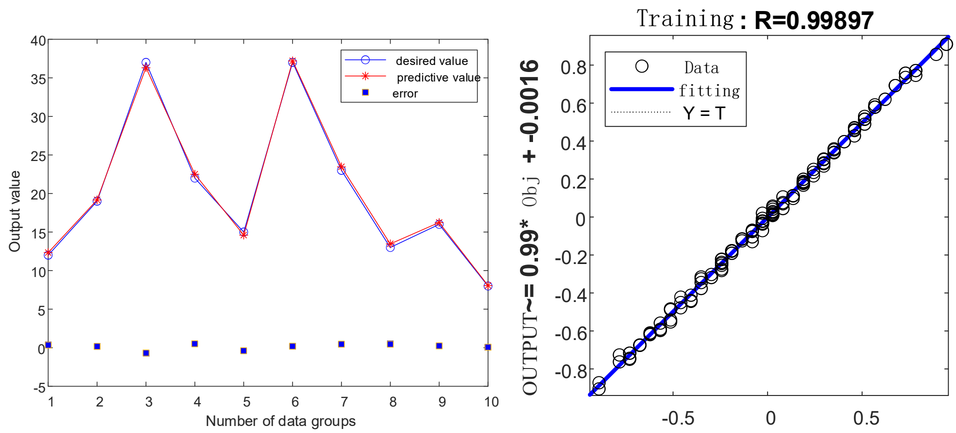
Over the past five years, a total of 300 datasets have been collected, with 70% selected as the training set and 30% as the testing set. Table 1 present 10 of these datasets.

Table 1 Partial dataset

Data type	*Number*	*School*	*Enterprise*	*Other subjects*	*System*	*System*	*Frequency*	*Intensity*	*School training*	*Enterprise employment*	*Talent*	*Evaluation results*
Training set	1	0.04	–0.85	0.87	–0.73	–0.78	–0.19	–0.75	–0.73	0.65	0.42	0.73
	2	–0.92	0.20	–0.68	0.05	–0.27	–0.16	–0.51	0.20	0.44	–0.23	0.52
	3	–0.36	–0.48	0.76	–0.54	–0.67	–0.78	–0.76	0.95	0.33	0.95	0.99
	4	0.92	0.53	–0.50	0.69	0.18	–0.12	0.52	–0.40	0.16	0.57	–0.85
	5	0.11	0.22	–0.69	–0.01	0.91	–0.28	–0.61	–0.05	–0.33	0.39	–0.46
	6	0.65	–0.82	0.28	0.64	0.40	0.14	0.46	0.05	0.11	0.98	–0.44
	7	–0.24	–0.46	–0.08	–0.82	–0.63	–0.42	–0.96	0.28	0.84	–0.14	–0.77
Test set	8	0.50	0.52	–0.81	0.68	–0.95	0.56	0.74	0.61	0.67	0.64	–0.92
	9	0.64	0.57	–0.60	–0.14	–0.37	–0.39	0.28	–0.88	0.27	0.86	–0.22
	10	–0.54	0.57	0.93	–0.40	0.85	–0.39	0.55	0.70	0.27	0.36	0.25

Based on the actual data, the BP neural network was trained, and it's fitting results are as follows:

Figure 4 Fitting results of the BP neural network. (a) Fitting results across different data groups, showing that the method achieves good dynamic tracking performance. (b) Regression curve between predicted and actual values, confirming the fitting effectiveness with high correlation (R = 0.99897) (see online version for colours)



(a) (b)

Figure 4 shows the training results of the BP neural network, where

a presents the fitting results, indicating that the method has good dynamic tracking performance

b the regression curve further confirms the fitting effectiveness.

4 Discussion

Industry-education integration has emerged as a key national development strategy in China, driven by the dual forces of advancing intelligence and 're-industrialisation'. It serves as an effective approach to address the pressing challenges of interdisciplinary technological development and the limited knowledge base and insufficient practical skills of talent in the modern era. Both domestic and international scholars and industry experts have conducted extensive and in-depth research on this topic, examining its entire lifecycle – including its key entities, environment, processes, and outcomes.

However, as a form of social systems engineering, industry-education integration involves complex interactions and couplings among various elements throughout its lifecycle. This inherent complexity makes it challenging to describe and characterise using traditional mathematical models. Consequently, the evaluation and development of industry-education integration often rely on empirical methods and statistical data, which lack the precision needed to inform effective policy adjustments.

To address this challenge, this paper proposes an evaluation method based on the BP neural network. By iteratively mapping relationships across multiple neurons and adjusting weights through feedback correction, the BP neural network effectively fits nonlinear functions, enabling precise evaluation of industry-education integration. The proposed framework is built around four primary indicators representing the entire lifecycle of industry-education integration, which are further expanded into 10 secondary indicators. These indicators constitute the input layer, while the evaluation results from the output layer.

A simulation model was developed and tested in the MATLAB environment using operational data from a vocational college collected over the past five years. The results validate that the proposed model exhibits strong dynamic tracking performance and high fitting accuracy, providing a robust foundation for precise evaluation and policy optimisation in industry-education integration.

5 Conclusion

This paper focuses on the integration of industry and education, with a particular emphasis on developing a career-oriented training model based on BP neural networks. It proposes a data-driven evaluation framework rooted in BP neural networks and validates the model's effectiveness using real-world data from a vocational college within a MATLAB environment. The study begins by highlighting the significance of career-oriented vocational education and the challenges it faces, underscoring the practical importance of advancing industry-education integration. It then conducts a comprehensive review of cutting-edge trends in industry-education integration both domestically and internationally, revealing that current integration efforts largely rely on empirical methods rather than robust data-driven approaches.

Building on this, the paper delves into the core concepts, foundational theories, and component boundaries of industry-education integration in vocational education. It analyses the current status and underlying issues within China's vocational education system, identifying gaps and challenges that hinder effective integration. Additionally, it explores the construction of an ecosystem for career-oriented training under the framework of industry-education integration, emphasising that the absence of precise evaluation methods often leads to an incomplete and inefficient ecosystem.

To address these gaps, the paper adopts BP neural networks as a tool for achieving more accurate, data-driven assessments of integration. It introduces the basic principles of BP neural networks, constructs a neural network model based on 10 secondary indicators, and conducts simulations and validations using actual operational data from a vocational college. The results demonstrate that the proposed model delivers strong dynamic tracking performance and high fitting accuracy, showcasing its potential as a robust tool for optimising industry-education integration and supporting the development of career-oriented training models.

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Conflicts of interest

The author declares no conflicts of interest.

Data availability statement

The data and code used in this study are available from the corresponding author, Huang Hao, upon reasonable request.

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