The Impact of Artificial Intelligence on Human Capital Formation in Digital Trade: Evidence from China

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Abstract: The rapid development of artificial intelligence increases the demand for interdisciplinary human capital in digital trade. It also challenges the formation of human capital in digital trade. This paper systematically examines the current scale and structural composition of digital trade human capital in the context of artificial intelligence. It identifies several key problems in the process through which universities form digital trade human capital. These include relevant curricula lagging behind technological development, inadequate digital education infrastructure, and alienation in the human–machine relationship during the training process. Building on this analysis, this paper examines the effect of artificial intelligence on the formation of digital trade human capital. It conducts an empirical test using panel data from 30 provinces in China from 2012 to 2023. The results show that artificial intelligence significantly increases the supply of digital trade human capital. In addition, industrial development and public education investment play significant roles in promoting the formation of digital trade human capital in universities. Based on these findings, this paper proposes systematic measures to address the main challenges facing higher education in digital trade. These measures are developed from the perspective of collaboration among university, industry, and public institution.

Keywords: Artificial Intelligence; Digital Trade; Higher Education; Human Capital; Triple Helix

1. Introduction

The development of digital technologies ushers in the era of digital intelligence and gives rise to the digital economy as a new economic form. This transformation further drives the rapid growth of digital trade. As a new critical arena for international competition, digital trade significantly promotes the cross-border integration of frontier technologies and enables the efficient allocation of high-quality digital factors. It improves production efficiency and international competitiveness and injects new momentum into economic growth. At the same time, the rapid iteration of digital technologies such as big data, cloud computing, and artificial intelligence continuously expands the tradable boundaries of digital products and services. This process further deepens the development of digital trade and generates a strong demand for interdisciplinary human capital in related fields. In this context, the imbalance between the supply and demand of human capital becomes a key constraint on the deepening development of digital trade [1].

As one of the most representative economies in the development of digital trade, China faces similar challenges. With the continuous evolution of digital trade and the rapid transformation of digital technologies, China still shows weaknesses in human capital reserves and core technological innovation that support long-term development. In response, the Ministry of Human Resources and Social Security of the People's Republic of China released the Action Plan for Accelerating the Cultivation of Digital Talent to Support the Development of the Digital Economy (2024–2026) in April 2024. The plan explicitly identifies the shortage of digital talent and outlines a three-year initiative to expand the supply of human capital. At the same time, digital technologies represented by artificial intelligence achieve major breakthroughs in foundation models, algorithm optimization, and computing infrastructure. These advances significantly enhance application efficiency and reveal strong transformative potential. The rapid development of artificial intelligence reshapes the digital trade ecosystem from multiple dimensions. It alters the demand structure for labor in related industries, drives adjustments in policy design, and creates new requirements for the formation of digital trade human capital in universities [2,3]. Moreover, the diffusion and integration of artificial intelligence into the education sector introduce both new opportunities and challenges for higher education in digital trade [4].

Therefore, this paper examines the impact of artificial intelligence on the formation of digital trade human capital. First, it reviews the scale and structural characteristics of digital trade human capital in the context of artificial intelligence. It then identifies the main constraints faced by universities in the formation process and analyzes the influence of artificial intelligence on digital trade human capital formation. Second, the paper constructs a fixed-effects model using panel data from 30 Chinese provinces from 2012 to 2023. The model tests the impact of artificial intelligence on the formation of digital trade human capital. Finally, drawing on the collaborative logic of the Triple Helix model and the empirical results, this paper proposes policy measures to optimize the formation of digital trade human capital through artificial intelligence. These measures address key barriers in digital trade higher education. The aim is to provide new perspectives and practical pathways for the high-quality development of digital trade human capital.

2. The Scale and Structure of Digital Trade Human Capital in China in the Era of Artificial Intelligence

China achieves a leading position in the research and application of artificial intelligence. According to the 2025 China Digital Trade Development Report, a total of 45,000 generative AI patents were filed worldwide in 2024, with China accounting for 61.5%, or 27,000 patents. At the same time, artificial intelligence becomes a key engine of China's digital economy. The core AI industry reaches nearly RMB 600 billion in 2024. This scale doubles relative to 2020. China also builds a relatively complete "AI+" industrial system. This system drives large-scale industrial upgrading and continuously generates new sources of economic growth. In the trade sector, the application of artificial intelligence connects the entire international trade chain and digitalizes all processes. It drives digital trade toward greater digitalization and intelligence and profoundly affects both the demand for and the structure of digital trade human capital.

According to human capital theory, human capital in the digital trade sector can be classified into general human capital and specific human capital. General human capital mainly exists in the application ecosystem of digital trade, such as e-commerce operations. Its key characteristic is the transferability of skills. In contrast, specific human capital is mainly concentrated in the core sectors of digital trade, such as R&D and software engineering positions. The knowledge and skills involved are highly specialized and difficult to transfer across industries. Therefore, we measure digital trade human capital from a dual-dimensional perspective. First, specialized human capital is measured by the sum of the full-time equivalent of R&D personnel and the number of employees in the information transmission, software, and information technology service industries [5]. Second, general human capital is measured by the number of employees engaged in e-commerce. The data come from the China Statistical Yearbook and the China E-Commerce Development Report 2022.

Breakthroughs in digital technologies significantly expand the demand for digital trade human capital and reshape its demand structure. As shown in Figure 1 and Figure 2, the overall scale of digital trade human capital in China increases steadily from 2013 to 2023. The scale of general human capital remains significantly larger than that of specialized human capital. Its growth follows a stepwise upward trend. Although remote work during the COVID-19 pandemic stimulates short-term expansion. However, the long-term growth rate gradually slows and approaches industry saturation. In contrast, specialized human capital in digital trade maintains stable growth. Overall, under the background of artificial intelligence, the demand for digital trade human capital shows clear structural change. It shifts from simple scale expansion toward a stage characterized by structural optimization. The demand type also shifts from digital application-oriented human capital to high-technology composite human capital [6]. At the same time, a significant human capital gap persists in the core sectors of the digital trade industry. This gap creates new challenges and requirements for the formation model of digital trade human capital in universities.

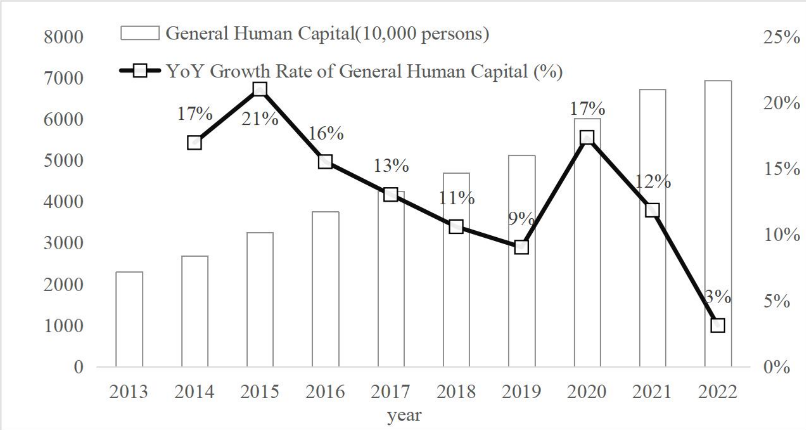

Figure 1. The Scale of General Human Capital in China's Digital Trade, 2013–2022
Source: E-commerce Development Report, 2022

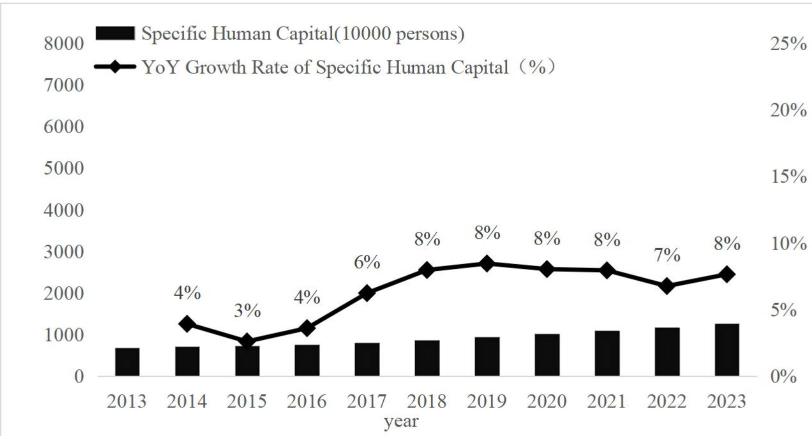

Figure 2. The Scale of Specific Human Capital in China's Digital Trade, 2012–2023
Source: China Statistical Yearbook

3. Challenges for Higher Education in Digital Trade

3.1 Lagging Curriculum Design

At present, the development of relevant training systems in Chinese universities remains at an early stage. Existing curricula show clear lags in both content design and structural arrangement. They struggle to meet the growing demand for highly skilled and interdisciplinary talent in digital trade [7]. The Ministry of Education of the People's Republic of China states in the Teaching Standards for the Major of International Economics and Trade that universities should strengthen students' digital literacy and ensure systematic training in digital trade theory and practice. However, many universities have not effectively implemented these requirements in their curricula. In terms of course content, some universities add digital trade–related courses within the traditional framework of international trade theory. Yet, these courses mostly focus on business processes or platform operations. They do not systematically integrate the applications of digital technologies such as big data, blockchain, or artificial intelligence in the trade sector. They also do not establish a comprehensive system for cultivating digital literacy, digital skills, and digital competence. This incremental approach to course integration constrains the effective formation of digital trade human capital. As a result, universities' human capital supply struggles to meet the industry's demand for interdisciplinary skills [8].

3.2 Practical Constraints in the Digital Transformation of Education

The digital transformation of education provides a crucial foundation for universities to cultivate digital trade human capital. Yet, the digital transformation of Chinese universities faces multiple constraints [9]. First, as a key material and technological support for the formation of digital trade human capital, digital education infrastructure still shows clear shortcomings. Some universities still use outdated simulation software with limited functionality in practical teaching. These systems are mainly local and standalone, showing a significant gap compared with current cross-border e-commerce platforms and SaaS tools that rely on big data, cloud computing, and platform-based operations. Consequently, they cannot realistically replicate the business environment and operational logic of digital trade. Second, the cultivation of digital trade talent places higher demands on teachers' digital literacy and practical capabilities. Full-time faculty need not only a solid theoretical foundation but also the ability to continuously track the development of new technologies, emerging business models, and innovative practices. They are also expected to engage in technology research and provide services to society. Nevertheless, many faculty members lack relevant experience and technical background in digital trade. Their understanding and application of frontier digital technologies remain limited. This limitation constrains their ability to guide students in understanding development trends and skill requirements in digital trade. Overall, deficiencies in both digital infrastructure and faculty capability weaken the efficiency and quality of digital trade human capital formation in universities.

3.3 Alienation in Human–Machine Interaction during Training

Digitalization of education has become a key trend in higher education. The application of digital technologies in cultivating digital trade human capital continues to deepen. However, excessive reliance on digital technologies in teaching can lead to alienation in human–machine interaction. This may weaken the central role of humans in educational activities and divert attention from the core goal of high-quality formation of digital trade human capital. On the one hand, digital trade is inherently uncertain and subject to real-world fluctuations. Digital twin simulations based on existing data allow students to learn specific operational processes and improve their problem-analysis and scenario-judgment skills to some extent. Yet, these simulations remain limited in helping students deeply understand business logic, institutional contexts, and real-world situations [10]. On the other hand, the development of digital education also requires teachers to reconsider their role in teaching. Excessive reliance on technological tools may weaken their leadership in curriculum design, value guidance, and skill development. It can also lead to neglecting the cultivation of students' creativity and critical thinking, thereby diverting attention from the goal of enhancing the quality of digital trade human capital [11].

4. Theoretical Analysis and Hypothesis Development

4.1 Mechanism Analysis of Artificial Intelligence on the Formation of Digital Trade Human Capital

4.1.1 Direct mechanism

The development of artificial intelligence introduces new skill-structure requirements for digital trade human capital. On one hand, AI significantly raises the skill threshold for positions in the digital trade sector. Its automation and intelligent features replace low-end, repetitive tasks. Work content shifts from standardized, execution-oriented tasks to complex cognitive tasks such as information integration, scenario analysis, and rule application. This shift gradually establishes a new work model characterized by human–machine collaboration [12,13]. In this context, digital trade human capital must not only possess solid knowledge of international trade but also demonstrate digital literacy and the ability to apply digital technologies. On the other hand, the ongoing evolution of artificial intelligence increases the demands on individual learning and adaptability. In the context of rapid technological change, practitioners need human–machine collaboration skills and the ability to apply AI in practice. In addition, they must develop continuous learning capacity, digital innovation skills, and the ability to integrate technologies [14]. Consequently, digital trade human capital goes beyond basic digital skills. It exhibits a progressive structure from digital literacy to digital skills and then to advanced digital capabilities. This structure enables it to meet the development demands of AI-driven digital trade.

4.1.2 Indirect mechanism

Artificial intelligence enhances the efficiency of cultivating digital trade human capital by optimizing the allocation of educational resources and reducing the cost per trainee. First, generative AI shifts educational practice from small-scale, experience-driven instruction to scalable, replicable, and highly personalized teaching models. It has a technical advantage in providing real-time feedback for content generation and learning-path recommendation. This helps overcome time and space constraints, while also improving the efficiency and scalability of educational resources [15]. Second, digital twin technology creates virtual teaching environments to systematically simulate real-world trade scenarios. It covers the full range of business processes, from micro-level operations to macro-level system management. Moreover, compared with traditional practical teaching, digital twin technology also reduces fixed costs such as site construction, platform collaboration, and external resource investment. It further enhances the replicability and scalability of practical instruction, thereby lowering the average cost of training [16]. Finally, the embedding of artificial intelligence helps reconstruct teachers' labor structure. It frees teachers from repetitive and procedural teaching tasks and reduces the time and effort required in the teaching process. This allows more teacher resources to be allocated to instructional design and capability development, thereby improving the efficiency of resource allocation in teaching [17].

Artificial intelligence also improves the quality of digital trade human capital by enhancing its capability structure. First, artificial intelligence promotes a shift in the role of teachers from traditional knowledge transmitters to capability builders. It also encourages a transformation in educational goals, moving from simple knowledge delivery toward a capability-oriented training model [18]. This shift helps strengthen students' problem-solving ability and their capacity for integrated knowledge application. Second, artificial intelligence promotes a shift in the mode of knowledge production from a linear and closed traditional structure to a generative and open structure. It facilitates interdisciplinary knowledge integration and dynamic recombination. This open knowledge generation model provides a more diverse knowledge base for the formation of digital trade human capital. It also enhances their technological innovation capability and their ability to handle complex tasks [19,20]. Finally, artificial intelligence has formed a learning model characterized by human–machine collaboration. Students can use artificial intelligence tools to conduct problem exploration, refine their logic, and optimize solutions based on their own learning needs. This process strengthens their capacity for independent exploration and innovative practice [21].

In summary, and as illustrated in Figure 3, artificial intelligence exerts a systematic promoting effect on the formation of digital trade human capital. Therefore, we propose the following hypothesis:

H1: Artificial intelligence promotes the formation of digital trade human capital.

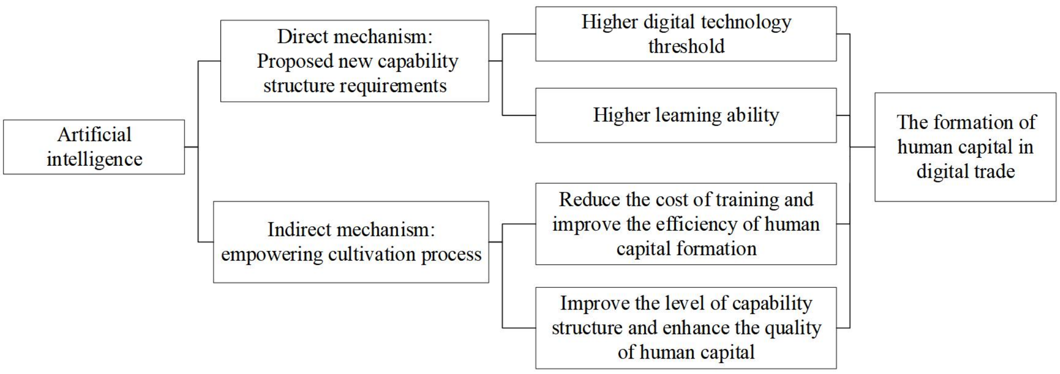

Figure 3. Mechanism of the Impact of Artificial Intelligence on Human Capital Formation in Digital Trade

4.2 A Triple Helix Perspective on Digital Trade Human Capital Formation in the Era of Artificial Intelligence

In the era of artificial intelligence, digital trade exhibits rapid technological upgrading, complex application scenarios, and dynamic evolution of institutional rules. Traditional discipline-centered education models struggle to support the structural optimization and capability upgrading of digital trade human capital [22,23]. In this context, universities alone cannot sustain the supply of high-quality human capital, necessitating effective support from government and industry at both institutional and practical levels [24]. The Triple Helix model, proposed by Etzkowitz and Leydesdorff, provides a theoretical explanation for such coordination. It illustrates that, in the knowledge economy, universities, industry, and government do not operate independently; rather, they interact through complementary functions and jointly drive the dynamic evolution of innovation systems [25]. Therefore, within the Triple Helix framework, the formation of digital trade human capital is no longer a linear supply process within the education system. Instead, it is shaped by the combined effects of institutional support, knowledge production, and market demand feedback. As shown in Figure 4, the government optimizes the talent development environment through institutional provision and policy support, industry strengthens capability matching by releasing real market demand and providing practical scenarios, and universities assume core functions in capability development and knowledge integration. The interaction of these functional roles collectively promotes the formation of digital trade human capital. Based on the above discussion, the following hypotheses are proposed:

H2a: Government support promotes the formation of digital trade human capital.

H2b: Industry development promotes the formation of digital trade human capital.

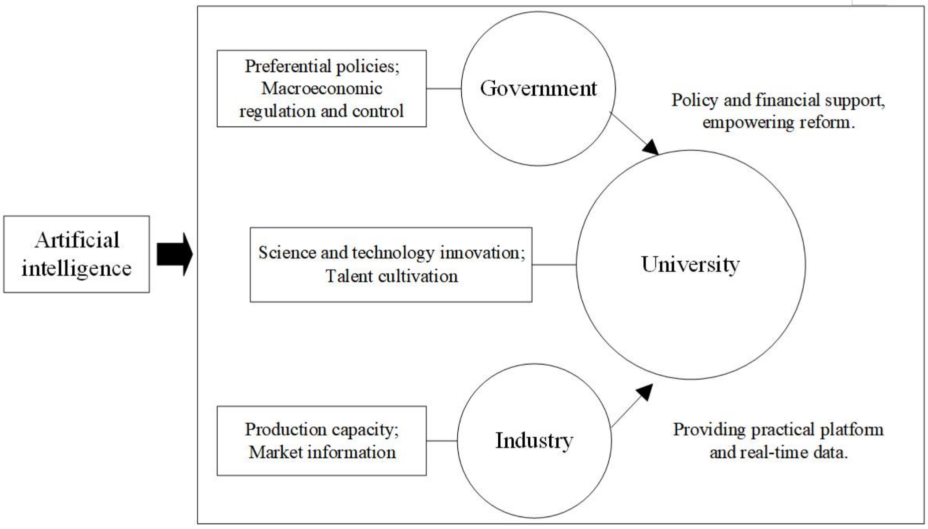

Figure 4. Government and Industry Driving University Human Capital Formation in Digital Trade under Artificial Intelligence

5. Methodology

5.1 Model Construction

To examine the impact of artificial intelligence on the formation of digital trade human capital, we construct a fixed-effects model, as shown in equation (1):

$$DTHC_{it}=\alpha + \beta_1 AI_{it} + \beta_2 GEI_{it} + \beta_3 ID_{it} + \gamma_2 \sum X_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (1)$$

Where i and t denote province and time. DTHC represents a proxy for the formation of digital trade human capital; AI denotes the level of artificial intelligence development; GEI indicates the level of government investment; ID captures the level of industry development; X is a set of control variables; δ and η represent province and year fixed effects, respectively; ε is the random error term; β and γ are the parameters to be estimated.

5.2 Measures

The dependent variable is digital trade human capital (DTHC). We measure the scale of digital trade human capital in core regional industries by the sum of the number of employees in the information transmission, software, and information technology services sector and the full-time equivalent of R&D personnel. Since the formation of human capital is ultimately reflected in the accumulation of human capital within core industries over a certain period, this paper uses this indicator as a proxy for the formation level of digital trade human capital.

The key independent variable in this paper is the level of artificial intelligence development (AI). Following Ma et al., an evaluation index system is constructed from four dimensions: the development environment of artificial intelligence, artificial intelligence innovation capability, artificial intelligence technological outputs, and the application of artificial intelligence technologies [26]. The specific indicators for each dimension are presented in Table 1. The entropy method is employed to assign weights and measure the level of artificial intelligence development across provinces.

Table 1. Indicators for Measuring the Development Level of Artificial Intelligence

Primary Indicators	Secondary Indicators	Tertiary Indicators	Specific Measures
Artificial intelligence development environment	Industrial foundation	Total economic output	Gross domestic product by region
		Share of secondary and tertiary industries	GDP index of secondary industry
			GDP index of tertiary industry
		Number of artificial intelligence enterprises	Number of legal entities in the information transmission, computer services, and software industry
	Policy support	Government intervention	General budget expenditure
Artificial intelligence innovation capability	Innovation environment	Technology transaction capability	Technology market transaction volume
	Innovation investment	Total investment in artificial intelligence	Total AI investment by listed companies in each province
		Employment in AI industry	Number of employees in information transmission, computer services, and software industry
		R&D expenditure	Internal expenditure on R&D in high-tech industries by region
Artificial intelligence technological outputs	Technological inventions	Number of valid invention patents	Number of valid invention patents in high-tech industries by region
		Number of transferred invention patents	Number of transferred patents and licenses from universities by region
	Scientific publications	Number of scientific papers	Number of scientific papers published by universities in each region
Application of artificial intelligence technologies	Application and commercialization	Number of new products put into production	Number of new product development projects in high-tech industries by region
			Sales revenue of new products in high-tech industries by region
		AI Technology transformation expenditure	Expenditure on technology transformation in high-tech industries by region

Another independent variable is government education investment (GEI). It is measured by provincial government expenditure on education, and the value is transformed into its logarithmic form. This indicator reflects the level of resource support provided by local governments for the education sector. Higher education investment can provide direct financial support for universities to develop digital trade-related programs, curriculum design, and practical training, thereby strengthening the foundation of human capital cultivation from the supply side [27]. Therefore, government education investment can serve as a proxy for the government helix in the Triple Helix model.

A further independent variable is industry development (ID). It is measured by the e-commerce sales of each province. This indicator reflects the development level of the digital trade industry. A well-developed e-commerce industry continuously generates demand for digital trade-related jobs, including operations, marketing, data analysis, and digital technology application, thereby driving the formation of digital trade human capital from the demand side. At the same time, the rich practical scenarios provided by industry promote the deep integration of knowledge and technology in practice and exert a guiding influence on the capability structure of human capital [28]. Therefore, the level of e-commerce development can serve as a proxy for the industry helix in the Triple Helix model.

In addition, we include the following control variables. (1) Labor force size (LFS). It is measured by the population aged 15–64 in each province. The value is transformed into its logarithmic form. (2) Economic development (ED). It is measured by the index of GDP per capita for each province. (3) Digital infrastructure (DI). It is measured by the number of internet broadband access ports in each province. (4) Number of enterprises engaged in e-commerce transactions (NEE). It is measured by the number of enterprises with e-commerce transaction activities in each province.

5.3 Data and Sample

This paper uses panel data from 30 provinces in China from 2012 to 2023. The data are mainly obtained from the CSMAR database, the ESP database, the CEInet statistics database, and the China Science and Technology Statistical Yearbook. Missing values are supplemented using the linear interpolation method. The descriptive statistics of the variables are reported in Table 2.

Table 2. Descriptive Statistics

Variable	Obs	Mean	p50	Std. Dev.	Min	Max
DTHC	360	0.242	0.141	0.287	0.00900	1.736
AI	360	0.0830	0.0450	0.108	0.00600	0.754
GEI	360	15.89	15.94	0.669	13.88	17.51
ID	360	5.289	2.447	8.113	0.0230	53.15
LFS	360	10.30	10.19	1.081	8.133	14.07
DI	360	2.524	2.047	1.963	0.106	10.39
ED	360	106.5	106.7	2.614	96.40	113.8
NEE	360	0.342	0.183	0.416	0.00400	2.808

6. Results

6.1 Baseline Regression Analysis

Table 3. Baseline Regression Analysis

	(1)	(2)	(3)	(4)	(5)
	DTHC	DTHC	DTHC	DTHC	DTHC
AI	1.438***	1.425***	1.429***	1.419***	1.408***
	(0.128)	(0.121)	(0.120)	(0.177)	(0.217)
GEI	0.072***	0.052*	0.046*	0.045**	0.044**
	(0.025)	(0.027)	(0.025)	(0.021)	(0.020)
ID	0.005***	0.005***	0.005***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LFS		0.073*	0.088**	0.090**	0.091**
		(0.040)	(0.039)	(0.035)	(0.034)
ED			0.002	0.002	0.002
			(0.001)	(0.001)	(0.001)
DI				0.001	0.000
				(0.008)	(0.006)
NEE					0.008
					(0.030)
_cons	-1.041**	-1.454***	-1.712***	-1.716***	-1.698***
	(0.391)	(0.450)	(0.516)	(0.520)	(0.523)
Provence fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360
R^2	0.942	0.942	0.943	0.943	0.943
adj.R^2	0.939	0.940	0.940	0.940	0.940

Notes: standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1

Table 3 presents the baseline regression results of the impact of artificial intelligence development on the formation of digital trade human capital. Column (1) reports the results without any control variables. Columns (2) to (5) gradually include the relevant control variables. The results show that the coefficient of AI on DTHC is positive and significant at the 1% level. This indicates that artificial intelligence significantly promotes the growth of human capital in core digital trade industries. In other words, artificial intelligence effectively facilitates the formation of digital trade human capital, thus supporting hypothesis H1.

In addition, as shown in columns (2) to (5), the regression coefficients of GEI on DTHC are all significantly positive. This result indicates that increased education investment effectively promotes the growth of digital trade human capital, thereby supporting Hypothesis H2a.

Furthermore, in Columns (2) to (5), the coefficient of ID on DTHC is positive and statistically significant at the 1% level. This indicates industry development contributes to the accumulation of digital trade human capital, thereby supporting Hypothesis H2b.

Moreover, regarding the control variables, the coefficient of LFS in Columns (2) to (5) is positive and statistically significant. This indicates that labor endowment is a fundamental condition for the formation of digital trade human capital.

6.2 Robustness Test

To examine the robustness of the baseline regression results, we conduct several robustness checks. (1) the estimation method is changed.

The model is re-estimated using OLS while controlling for province and year fixed effects. As shown in column (1) of Table 4, the estimated coefficients of AI, GEI, and ID remain positive and significant. (2) A one-period lag regression is performed. The three explanatory variables are lagged by one period and re-estimated. As reported in column (2) of Table 4, the lagged terms (L.AI, L.GEI, and L.ID) remain significantly and positively associated with digital trade human capital. (3) a winsorization procedure is applied. All continuous variables are winsorized at the 1% level at both tails before re-estimation. As shown in column (3) of Table 4, the direction, magnitude, and significance of the core explanatory variables remain largely unchanged. Overall, the positive effect of artificial intelligence on the formation of digital trade human capital is robust. The promoting roles of government education investment and industry development are also robust.

Table 4. Robustness Checks

	(1)	(2)	(3)
	DTHC	DTHC	DTHC
AI	1.408***		1.408***
	(0.123)		(0.255)
GEI	0.044***		0.051**
	(0.016)		(0.023)
ID	0.004***		0.005***
	(0.001)		(0.002)
L.AI		1.533***	
		(0.163)	
L.GEI		0.043**	
		(0.019)	
L.ID		0.005***	
		(0.002)	
_cons	-1.358***	-2.163***	-1.728***
	(0.340)	(0.617)	(0.466)
Control variables	Yes	Yes	Yes
Provence fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
N	360	330	360
R^2	0.993	0.942	0.936
adj.R^2	0.992	0.939	0.932

Notes: standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1

7. Conclusions

This paper uses panel data from 30 Chinese provinces over the period 2012–2023. It empirically examines the multidimensional driving mechanisms behind the formation of digital trade human capital. First, the development of artificial intelligence has a positive effect on digital trade human capital formation (H1). Second, this paper finds that government education investment effectively supports the formation of digital trade human capital (H2a). Finally, this paper reveals that industry development significantly promotes the formation of digital trade human capital (H2b).

8. Implications

First, universities should establish a talent cultivation system that integrates artificial intelligence with trade. On the one hand, universities should respond to the growing demand for human capital in digital trade. This requires systematic optimization of the curriculum structure and the integration of artificial intelligence into the digital trade teaching system. While strengthening the theoretical foundation of digital trade, universities should allocate modules on artificial intelligence applications in a balanced manner. This approach helps achieve coordinated optimization of the curriculum structure. At the same time, artificial intelligence application scenarios should be incorporated into practical training in digital trade. Such integration would strengthen students' digital literacy and technological application capabilities in real industrial environments and improve the structure of their composite skills. On the other hand, universities should promote deeper integration between artificial intelligence and trade disciplines. They could explore interdisciplinary training programs that offer a dual bachelor's degree in artificial intelligence and trade. Such programs would expand the supply of innovative and interdisciplinary talent. They would also better align with the upgrading demand for skill structures in core digital trade industries. In addition, universities could establish regular university–industry collaboration mechanisms. They could invite industry experts with practical experience in digital trade to deliver specialized lectures or provide practical guidance on a regular basis. This approach would promote dynamic alignment between technological frontiers and teaching content.

Second, the digitalization of education should be promoted. The government should strengthen policy support and provide dedicated funding to support human capital formation in digital trade.

Such support would guide universities to accelerate the development of digital teaching infrastructure and the upgrading of relevant courses. Universities should also deepen collaboration with artificial intelligence firms. They could jointly develop practice-oriented teaching platforms tailored to digital trade programs. This approach would embed frontier technological applications into the teaching system and enhance the technological content and practical depth of the curriculum. In addition, universities should establish long-term and stable collaboration mechanisms with firms related to digital trade. They should incorporate real business data and technological application scenarios from these firms into practical training. This approach would enhance the real-world relevance and dynamic adaptability of the curriculum. Finally, universities should systematically promote the improvement of faculty AI literacy. They should organize continuous, tiered, and targeted AI training programs for relevant faculty members to establish a regular capacity-building mechanism. In addition, the outcomes of these programs should be quantitatively evaluated, with strengthened process monitoring and feedback. These measures would comprehensively enhance faculty members' AI application capabilities and the overall quality of digital teaching.

Third, universities should improve talent cultivation models that promote human–machine collaboration. They should establish a bidirectional "university–enterprise" training mechanism. Both sides should jointly build practice-based teaching platforms and promote the deep integration of theoretical education with industrial practice. This approach strengthens students' understanding of the operational mechanisms of digital trade and improves their ability to translate theoretical knowledge into practical application. At the same time, universities should encourage faculty members to participate regularly in industry research and exchange activities. Such engagement would help instructors track technological evolution and business model changes in the digital trade sector. It would also enhance the forward-looking orientation and adaptability of the teaching system. Then, during the teaching process, instructors should guide students to maintain cognitive agency in an AI-assisted learning environment. Students need to understand that artificial intelligence functions primarily as a tool. Instructors should also help students establish a clear awareness of cognitive division of labor in a human–AI collaborative learning framework. This approach strengthens problem identification, critical thinking, and innovation capabilities. As a result, artificial intelligence becomes an enabling tool that expands the boundaries of human capability rather than a substitute for human cognition.

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