International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-12

https://doi.org/10.70917/ijcisim-2026-1785
Article

Changes in demand and optimization of cultivation paths of smart financial talents for corporate carbon reduction and pollution reduction under the risk constraints of artificial intelligence application: a mixed research approach

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Abstract: Environmental pollution and climate change are major challenges on the road to sustainable development for human society. In this regard, based on the risk constraints of the application of artificial intelligence, this paper takes 2712 A-share listed manufacturing enterprises from 2012 to 2024 as research objects, and utilizes the mixed research method of qualitative combined with quantitative analysis to examine the impact of artificial intelligence on the reduction of pollution and carbon dioxide of enterprises, as well as the impact of carbon dioxide reduction and pollution reduction of enterprises on the demand for intelligent financial talents. The study shows that the application of artificial intelligence can effectively reduce the sulfur dioxide and carbon dioxide emissions of enterprises, and play the effect of pollution reduction and carbon reduction. The regression coefficients of the degree of demand for intelligent financial talents in enterprise pollution reduction and carbon reduction are 0.273 and 0.234 respectively, indicating that for every unit increase in pollution reduction and carbon reduction, the demand for intelligent financial talents in enterprises will increase by 0.273 and 0.234 units respectively. At present, the market demand for intelligent financial talents has formed a large gap, the traditional financial education training path, and can not meet the current economic and social demand for talents, there is an urgent need to explore the new path of high-quality training of intelligent financial talents.

Keywords: artificial intelligence; risk constraints; enterprise pollution reduction and carbon reduction; intelligent financial talents

1. Introduction

In today's society, the development of enterprises is no longer only concerned about the growth of economic interests, but also need to consider the process of production, production of products, service provision and other aspects of the realization of carbon reduction and pollution reduction, that is, in the protection of the environment, resource conservation under the premise of sustainable development [1-2]. In the green sustainable development of enterprises, the acceleration of economic integration makes enterprises face great pressure to reduce carbon and pollution. In this context, enterprises need to continuously improve the level of financial management to reduce costs, improve efficiency, and optimize resource allocation. The traditional enterprise financial management model has been unable to meet the needs of enterprise development, and enterprises need to seek new financial management models and technical means. And artificial intelligence (AI) as an emerging technology means, with powerful data processing and analysis capabilities, in the green sustainable development of enterprises can bring many advantages for financial management [3-5]. Through the introduction of AI technology, enterprises can realize real-time monitoring, intelligent analysis and prediction of financial data, thus improving the accuracy and timeliness of financial management [6-7]. AI technology can also help enterprises to realize the automatic identification and early warning of financial risks, which can provide powerful support for enterprise decision-making [8-9].

In this regard, Wang and Yang empirically analyzed the synergistic effect of digital intelligence transformation and financial innovation on the effectiveness of enterprise risk management based on the data of listed companies in China from 2011 to 2023, and pointed out that the effect of the two is mediated by partial mediation and is more significant in high information transparency enterprises [10]. Li and Liu analyze the application logic and governance challenges of big data and visualization technology in enterprise financial analysis in the era of digital intelligence, point out that intelligent visualization can drive data value mining and enhance management effectiveness, and emphasize the key supporting role of building a secure governance system for digital transformation [11]. Based on the theories of principal-agent and information asymmetry, Liu analyzed the inhibitory effect of industry-finance integration on the operation and financial risk of enterprises, pointed out that it significantly reduces the risk by improving the quality of internal control and the efficiency of resource allocation, and emphasized that this effect is more prominent in high-tech and high-financing constraint enterprises [12]. Tang analyzes the impact and application of AI on corporate financial management, noting that it can drive efficiency gains and reshape the finance function, and emphasizes the need for finance professionals to accelerate their transformational positioning to adapt to intelligent change [13]. Hornuf and Schaefer analyzed the advantages of machine learning in corporate financial forecasting, pattern discovery and causal inference, pointing out its ability to efficiently process unstructured data and nonlinear relationships to enhance quantification, and highlighting mergers and acquisitions and default prediction as representative of the promising directions [14]. Xin constructs an AI keyword index based on A-share data and text analysis from 2010 to 2023, and empirically points out that AI significantly reduces corporate financial risk by alleviating financing constraints and investment inefficiencies, and emphasizes that the effect is more prominent among non-SOEs and low-leveraged firms [15]. Liu analyzes the transformation path of big data-driven financial management in terms of intelligent analysis and risk monitoring, and points out through case studies that it can accurately identify trends and optimize resource allocation, thus emphasizing the key role of data empowerment in enhancing the effectiveness of internal control and enterprise competitiveness [16]. Ajape and Adegbayibi analyzed the penetrating role of AI in the financial aspects of corporate capital budgeting, dividend policy and M&A decision-making based on theories such as preferential financing and technology acceptance model, and pointed out through the examination of examples that AI can optimize the efficiency of financing and strategic planning, and at the same time, emphasized that there are still some limitations in its application [17]. Roy et al. analyzed the dynamic optimization effect of AI on traditional valuation methods in the capital budgeting process such as NPV and real options, pointed out that it can improve the accuracy of cash flow estimation and scenario simulation through machine learning and prediction analysis, and emphasized that it is necessary to pay attention to the transparency of decision-making and the governance risk while enhancing the flexibility of financial strategy [18]. The above study reveals that AI can significantly reduce corporate financial risks and improve management effectiveness by alleviating financing constraints, optimizing resource allocation and improving internal control quality.

However, how to maintain professional ethics in finance with the help of financial intelligence has become an urgent problem for enterprises. Finance personnel need to always follow the professional code of ethics and ensure the fairness and compliance of decision-making in the process of intelligent transformation. Under this risk constraint, financial talents need to master relevant AI skills, including big data analysis, machine learning, deep learning, etc. By learning these skills, they can better understand and apply AI technology to improve work efficiency and professional competence [19-20]; and at the same time, they must have the ability to navigate the technical ethics and risk control logic brought about by AI, and to seek a balance between intelligent decision-making and responsibility [21]. Therefore, it is of great practical significance to explore the change in demand and optimization of cultivation path for intelligent financial talents under the risk constraints of AI application for corporate carbon reduction and pollution reduction. For the requirements of finance intelligent transformation on finance talents, Al-Harbi examined the reshaping effect of AI on finance professional duties through case study and historical traceability, pointing out that it both replaces traditional operations with automation and data analysis and empowers decision-making efficiency, and emphasized that practitioners need to meet the dual challenges of intelligent transformation through continuous learning and skill iteration [22]. Guo et al. analyzed the AI era Guo et al. analyzed the obstacles faced by financial education in the era of AI, such as outdated curricula and disconnected practices, pointed out that the cultivation of interdisciplinary composite talents needs to promote the modernization of teaching content and university-enterprise synergy, and emphasized that the construction of fintech labs and innovative pedagogies play a key role in adapting to the intelligent transformation of the industry [23]. Díaz-Santamaría et al. analyzed the enabling effect of the psychological education strategy integrating AI, emotional intelligence and financial intelligence on the digital transformation of the academic community based on the practice of the National University of Colombia workshop. Through theoretical lectures and gamified teaching, they pointed out that it could significantly enhance technological adaptability and the satisfaction of participants reached 4.7 points. They also emphasized that comprehensive skills training is the key path to meet the talent demands in the era of intelligence [24].

This paper first puts forward three research hypotheses based on theoretical analysis, takes 2712 A-share listed manufacturing enterprises from 2012 to 2024 as the research object, measures the level of artificial intelligence in manufacturing enterprises using the artificial intelligence word frequency of listed companies' annual reports, and carries out benchmark regression using the two-way fixed-effects model for the impact of artificial intelligence application on pollution reduction and carbon reduction of manufacturing enterprises. Then, the qualitative analysis method is used to specifically explore the impact of enterprise carbon reduction and pollution reduction on the demand for intelligent financial talents. Four major types of intelligent financial talent types are pointed out: intelligent financial analysts, intelligent financial architects, intelligent financial operators, and intelligent financial auditors, and the data are analyzed through Logit regression model constructs with the aim of exploring the changes in the demand for intelligent financial talent in the context of carbon reduction and pollution reduction in enterprises. On the basis of the results, the optimization of the training path of smart financial talents is proposed.

2. Research hypotheses

(1) The direct impact of artificial intelligence applications on the synergistic development of carbon reduction, pollution reduction, green expansion and growth of enterprises.

Artificial intelligence technology is led by scientific and technological innovation, integrating digitalization, intelligence, greening and other emerging technological production elements, breaking through the traditional production function constraints, reshaping the industrial form, operation mode and growth momentum. In the process of new industrialization, the advantages of digitization, intelligence and greening are used to build a green and low-carbon economic system, which is inherently consistent with the multi-objective balanced requirements of carbon reduction, pollution reduction, green expansion and growth.

The direct mechanism of the application of artificial intelligence on enterprise carbon reduction, pollution reduction, green expansion and growth is reflected in the following three aspects:

First, incubating new industries and empowering carbon reduction and pollution reduction.

The birth of new industries often depends on the “can not be” to “can be” technology leap, artificial intelligence technology attributes significantly better than the traditional path, embodied in higher energy efficiency and lower environmental load, those who are constrained by the bottleneck of the traditional technology can not realize the efficient development and use of clean energy. The clean energy that cannot be efficiently developed and utilized due to traditional technological bottlenecks can also be developed and efficiently utilized on a large scale. Emerging industries reduce the dependence on resources and environment, and economic growth and pollution are gradually decoupled, which in turn drives the green transformation of the whole industrial chain and reduces the intensity of carbon pollution.

Secondly, new models are generated to realize green transformation.

The optimal combination of production factors jumps up is one of the basic connotations of artificial intelligence, which completely changes the efficiency logic of the growth model by introducing data elements and reconstructing traditional factor relationships. With the support of AI technology, the economic growth model has transformed from linear sloppy to circular and efficient, resource allocation has been greatly optimized, and green emerging economies such as circular economy and sharing economy have become the mainstream mode of growth.

Thirdly, new kinetic energy has been nurtured to promote high-quality economic growth.

Different from the traditional “resource-dependent” and “labor-intensive” growth drivers, artificial intelligence is taken as the core driving force to enhance the total factor productivity and release the efficiency dividend through technological innovation, and to guide the flow of factors and resources to emerging industries through the reform of the policy system and market mechanism through institutional innovation, so as to contribute to high-quality growth. Through institutional innovation and reform of the policy system and market mechanism to guide the flow of factors and resources to emerging industries, providing the necessary support for high-quality development.

(2) Under the risk constraints of artificial intelligence application, the demand for intelligent financial talents is affected by carbon reduction and pollution reduction of enterprises.

With the rapid development and application of artificial intelligence, it also makes the enterprise risk increase sharply, and the demand for intelligent financial talents is more and more urgent. However, the current low penetration rate of smart finance has led to a contradiction between the supply and demand of talents. At the same time, in the context of carbon reduction and pollution reduction, the application of artificial intelligence as a form of advanced productivity led by scientific and technological innovation, its core connotation and green technological innovation is highly compatible with the carbon reduction and pollution reduction synergies provide a fundamental technical support and path guidance, the market demand for intelligent financial talents is becoming more and more exuberant. On the one hand, intelligent financial talents can create value co-creation and form a mutual win-win market, and data sharing is extremely important. On the other hand, the transformation of traditional financial decision-making into intelligent decision-making can effectively save the cost of labor, trial and error, production, etc., and realize the purpose of corporate carbon reduction and pollution reduction.

In summary, the application of artificial intelligence technology can improve the level of synergistic promotion of carbon reduction, pollution reduction, green expansion and growth of enterprises, and the strengthening of technological innovation capability and optimization of industrial structure layout are its important conduction pathways. And the risk constraints of AI application and the background of enterprise carbon reduction and pollution reduction jointly promote the market demand for intelligent financial talents. As a result, the article proposes the following research hypotheses:

Hypothesis H1: The application of artificial intelligence can positively influence the synergistic advancement of corporate carbon reduction, pollution reduction, green expansion and growth.

Hypothesis H2a: the application of artificial intelligence risk constraints, can improve the enterprise demand for intelligent financial talent enhancement.

Hypothesis H2b: the general background of enterprise carbon reduction and pollution reduction can improve the enterprise demand for intelligent financial talent enhancement.

3. Quantitative analysis of artificial intelligence and corporate carbon and pollution reduction

3.1. Variable Selection and Model Construction

3.1.1. Variable Selection and Data Sources

(1) Explained variables: pollution reduction ($\ln SO_2$) carbon reduction ($\ln CO_2$)

At present, the measurement of pollution reduction and carbon reduction is mostly based on sulfur dioxide emissions and carbon dioxide emissions as the main indicators, sulfur dioxide, as a typical air pollutant, is one of the two main pollutants in the Chinese government's pollution reduction targets, this paper selects the total amount of sulfur dioxide emissions to measure the level of pollution emissions from enterprises, and the data comes from the China Tax Survey data. The total carbon dioxide emissions of enterprises, i.e., carbon dioxide emissions per unit of gross industrial output value, is chosen as the alternative indicator of carbon emissions, and the logarithmic value is taken by adding 1.

(2) Core explanatory variable: artificial intelligence (AI)

The method of artificial intelligence word frequency in the annual reports of listed companies has advantages in terms of timeliness, comprehensiveness, accessibility, dynamics, market response and policy orientation, which can timely reflect the latest degree of attention and investment in artificial intelligence by enterprises. In this paper, we utilize Python open source “jieba” Chinese word segmentation module to segment the text of annual reports of listed companies, and take the natural logarithm of the number of AI keywords in the annual report plus one as a measure of the level of application of AI in enterprises.

(3) Control Variables

In order to reduce the impact of omitted variables on the explanatory power of the research model and the regression results of this paper that may produce bias, this paper selects enterprise size ($Size$), asset-liability ratio (Lev), enterprise growth ($Growth$), enterprise age (Age), board of directors' size ($Board$), whether the chairman of the board of directors and general manager of the board of directors are two positions in one ($Dual$), equity concentration ($Top1$), and technological innovation ($Lnallpats$) are eight control variables added to the regression model to obtain objective and accurate estimation results. The basic information and financial data of the enterprises are obtained from the database of Cathay Pacific Database (CSMAR).

3.1.2. Modeling

(1) Model construction

Regarding the impact of the application of artificial intelligence on enterprise carbon reduction and pollution reduction, the regression analysis model is as follows:

$$\ln SO_{2it} = \alpha + \beta \cdot AI_{it} + \sum_{j=2}^{k} \mu_j Control_{jit} + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

$$\ln CO_{2it} = \alpha_0 + \beta_0 \cdot AI_{it} + \sum_{j=2}^{k} \mu_{0j} Control_{jit} + \gamma_{0i} + \delta_{0t} + \varepsilon_{0it} \tag{2}$$

where i denotes the enterprise, t denotes time, SO_2 denotes sulfur dioxide emissions, i.e., pollution emissions from the enterprise, and CO_2 denotes carbon emissions. AI_{it} denotes the degree of AI application at time t enterprise i, and its coefficient β can reflect the effect of AI in reducing pollution and carbon. $Control$ denotes a series of control variables, γ_i denotes the enterprise fixed effect, δ_t denotes the time fixed effect, and ε_{it} denotes a random disturbance term.

3.2. Quantitative analysis results

3.2.1. Descriptive statistics of variables

This paper is based on 2,712 A-share listed manufacturing companies in China, with a sample period from 2012 to 2024. The annual reports, basic corporate information and financial data of listed companies are from the Cathay Pacific database (CSMAR). In order to ensure the quality of data, this paper treats the samples as follows: (1) excluding the companies in the financial industry; (2) excluding the information transmission, software and information technology service industry and the scientific research and technology service industry; (3) excluding the samples that are in the status of ST and *ST in the current year; and (4) excluding the samples with missing data.

The descriptive statistics of each variable are shown in Table 1.

Table 1. Descriptive Statistics of Variables

Variable	Symbol	N	Mean	SD	Min	Max
Reduce pollution	lnSO_4	2712	7.056	0.221	6.367	7.583
Reduce carbon emissions	lnCO_4	2712	11.231	1.834	0.114	17.572
Artificial intelligence	*AI*	2712	0.633	0.909	0.000	4.154
Enterprise scale	*Size*	2712	23.485	1.145	18.809	24.276
Enterprise growth potential	*Growth*	2712	0.181	0.288	-0.504	2.824
Asset-liability ratio	*Lev*	2712	0.426	0.148	0.087	0.835
Enterprise age	*Age*	2712	2.907	0.329	1.844	3.210
Board size	*Board*	2712	2.342	0.173	1.801	2.729
Two positions combined	*Dual*	2712	0.301	0.476	0.000	1.000
Equity concentration	*Top*1	2712	33.482	14.224	8.922	75.280
Technological innovation	*Lnallpats*	2712	1.675	1.834	0.000	8.181

The purpose of conducting the VIF test is to assess the degree of multicollinearity between the independent variables in the multiple linear regression model. According to the VIF test results in Table 2, the VIF values of all independent variables are less than 10, with the highest VIF value of 2.71, the lowest VIF value of 1.01, and the average VIF value of 1.43. This indicates that the current regression model is reasonable in the selection of independent variables, and that the influence of multicollinearity on the model is small.

Table 2. VIF Test Results

Variable	VIF	1/VIF	Variable	VIF	1/VIF
$\ln SO_4$	2.71	0.37	*Age*	1.07	0.93
$\ln CO_4$	2.61	0.38	*Board*	1.01	0.99
AI	1.37	0.74	*Dual*	1.08	0.93
Size	1.36	0.74	*Top*1	1.09	0.92
Growth	1.15	0.87	*Lnallpats*	1.21	0.83
Lev	1.13	0.88	Mean (VIF)	1.43	0.70

3.2.2. Benchmark regression analysis

The results of the benchmark regression of the impact of the application of artificial intelligence on enterprise pollution reduction and carbon reduction are shown in Table 3, which show that the application of artificial intelligence can effectively reduce enterprise sulfur dioxide and carbon dioxide emissions, and play the effect of pollution reduction and carbon reduction, with the regression coefficients of -0.004 and -0.024, respectively, and the preliminary validation of the research hypothesis 1. The estimated coefficient of enterprise size (*Size*) on carbon and pollutant emissions is positive, which means that the overall external demand of large-scale enterprises is larger, and the factor inputs and energy consumption involved also increase accordingly, so its carbon reduction effect may not be as significant as that of small-scale enterprises. The estimated coefficients of enterprise growth (*Growth*) and gearing ratio (*Lev*) on carbon emissions are positive, which means that enterprise growth, i.e., increase in revenue and gearing ratio, is not conducive to carbon emission reduction.

Table 3. Benchmark Regression Results

Variable	$\ln SO_4$	$\ln CO_4$
AI	-0.004***(-2.31)	-0.024**(-2.35)
Size	0.001(0.93)	0.785***(221.73)
Growth	-0.001(-0.79)	-0.024***(-2.35)
Lev	-0.004(-2.31)	0.041***(4.37)
Age	0.021***(5.37)	0.155***(10.12)
Board	-0.029***(-4.35)	0.089***(3.68)
Dual	0.000(0.15)	-0.079***(-6.83)
*Top*1	0.000(0.11)	0.007***(13.28)
Lnallpats	0.001***(2.74)	0.021***(8.83)
Constant	7.050***(313.48)	-13.037***(-121.09)
Observations	2712	2712
Adjusted R-squared	0.734	0.913
stkcd	YES	YES
year	YES	YES

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

The estimated coefficient of enterprise age (*Age*) is significantly positive, as the age of the enterprise grows, its carbon dioxide use efficiency will gradually decline, carbon emissions will increase, the weaker the ability to control the pollution emissions in the production process, and the ability to reduce pollution will decline. The size of the board of directors (*Board*) has a positive impact on carbon emissions, the board of directors may seek higher returns, to achieve "good results" in favor of personal performance evaluation, and then seek personal gain, ignoring those who need to invest a lot of money and slow to see the results of carbon emission reduction actions. The estimated coefficient on sulfur dioxide emissions is significantly negative. When the proportion of board members with environmental background is high, the effect of environmental investment in improving air quality will be more significant, and thus improve air quality.

Whether the chairman of the board and the general manager have two positions (*Dual*) is negatively related to carbon dioxide emissions, and the combination of the chairman and the general manager will promote the green technology innovation of the enterprise, which will have a positive impact on the carbon reduction of the enterprise. Combining the roles of chairman and general manager may lead to the lack of management supervision mechanism, which in turn affects the effective implementation of environmental policies and measures. Shareholding concentration (*Top*1) has a positive impact on carbon dioxide and sulfur dioxide, the lower the shareholding concentration, the higher the quality of environmental information disclosure, and environmental information disclosure will promote corporate carbon emission reduction and corporate green technological innovation and thus reduce pollution. The estimated coefficients of technological innovation (*Lnallpats*) on the explanatory variables are significantly positive, indicating that technological innovation brings more carbon and pollution emissions, and technological innovation brings performance enhancement and production expansion to enterprises, and production expansion may cause more energy consumption, which in turn generates more carbon dioxide and pollutants.

3.2.3. Robustness Tests

In order to strengthen the robustness of the benchmark regression results, this paper uses three methods to test them and the results are shown in Table 4.

The first is to add interaction fixed effects to control for multidimensional shocks. There may be heterogeneous effects of time shocks to different subjects in the real economic system, and AI may not have the same shocks to the synergistic benefits of different cities in the time dimension. Traditional two-way fixed effects models have limitations in dealing with endogeneity triggered by unobservable variables that vary both over time and with individuals. Panel interaction fixed effects models can simultaneously control for the joint effects of individual heterogeneity and time-varying variation, and eliminate the effects of some fixed but unobserved confounders on the causal estimation results. As can be seen from column (1) of Table 4, the regression coefficient of AI is 0.083 and significant at the 1% level. This result indicates that the results of the benchmark regression still hold after eliminating the possible negative effects of multidimensional time shocks and individual heterogeneity on the outcome estimates.

Table 4. Robustness Test Results

Variable	Interactive fixed effect	Ultra-efficient SBM	Construction of the experimental zone
	(1)	(2)	(3)
AI	0.083***	0.038***	1.134***
	(3.31)	(3.31)	(2.23)
Instrumental variable	-	-	-
Anderson canon.corr. LM	-	-	-
Cragg-Donald Wald F	-	-	-
Control variable	YES	YES	YES
Interactive fixed effect	YES	YES	YES
Urban fixed effect	YES	YES	YES
Time fixation effect	YES	YES	YES
Observed value	2712	2712	2712
R^2	0.582	0.136	0.278

The second is to replace the method of measuring the synergistic benefits of corporate pollution and carbon reduction in order to mitigate the bias of results caused by measurement differences. Reducing pollution and carbon means that sustainable economic growth is accompanied by emission reductions and efficiency gains. Improving the quality and efficiency of economic development means maximizing economic output with the smallest possible factor consumption, as well as lower negative environmental externalities, and focusing on improving green total factor productivity. According to the multi-input and multi-output characteristics of national economic production, this paper uses the super-efficient SBM model to re-measure the synergistic benefits in accordance with the practical ideas of the existing literature. As can be seen from column (2) of Table 4, the regression coefficient of the application of AI is 0.038 and significant at the 1% level, implying that the conclusion that AI promotes synergistic governance of pollution reduction and carbon reduction is valid.

Third, the proxy variable for the core explanatory variables is replaced to control the difference in the degree of application of AI technology in the economy and society. In this paper, the policy is used as a proxy variable for AI, and the multi-period double-difference method is applied to test it. As can be seen from column (3) of Table 4, the regression coefficient of the policy dummy variable on synergistic benefits is 1.134, and it is significant at the 5% level, indicating that the application of AI technology significantly promotes the reduction of pollution and carbon in enterprises, which proves Hypothesis 1 again.

4. Qualitative analysis of the need for carbon reduction and smart finance talent

4.1. Questionnaire design

This chapter will use qualitative analysis methods to specifically explore the impact of enterprise carbon reduction and pollution reduction on the demand for intelligent financial talents. The questionnaire consists of three parts: the first part is the basic information of the respondents, including the respondents' gender, age, years of working experience, education, professional background, job level, and the industry to which the enterprise belongs, the nature of the enterprise, and the size of the enterprise's annual revenue. The second part is the analysis of the demand for intelligent financial talents, including the degree of demand, type, knowledge background, etc. The purpose is to understand the specific demand for intelligent financial talents under the risk constraints of the application of artificial intelligence and the background of carbon reduction and pollution reduction of enterprises, aiming to provide a basis for the cultivation of intelligent financial talents. The survey object includes middle and senior managers of enterprises, and 183 valid questionnaires were returned.

4.2. Intelligent Finance Talent Demand Analysis

4.2.1. Sample statistics

The sample statistics of the demand for enterprise intelligent financial talents show that the willingness of enterprise financial talents to intelligent transformation, the proportion of 66.7% of those who chose “strong” or more, indicating that most of the surveyed enterprises have a strong willingness for intelligent financial talents. Financial intelligent transformation obstacles, with a strong willingness to financial intelligent transformation, 73.22% of the respondents chose “lack of talent”, indicating that intelligent financial talent is the key factor in the transformation of enterprise financial intelligence enterprise demand for intelligent financial talent, 77.60% of the respondents think that enterprises need Intelligent financial talents. Among them, 39.34% of the respondents said “very much in need”. In summary, it can be seen that the vast majority of enterprises have fully recognized the urgency of the transformation of financial intelligence, as well as the importance of intelligent financial talent in it.

Specifically in terms of the type of intelligent financial talent demand, intelligent financial analysts accounted for 72.68% ranked first, indicating that in the risk constraints of the application of artificial intelligence, as well as in the context of corporate pollution reduction and carbon reduction, enterprises need more financial personnel to master big data analysis and decision-making capabilities, and intelligent financial analysts able to visualize the presentation of financial reports. Intelligent financial operators accounted for 55.19%, ranking second, which is in line with the inward expansion and upgrading of accounting functions. In the era of artificial intelligence, the function of accounting has changed from traditional accounting to value creation, and financial personnel need to coordinate the overall situation, rely on technology to establish a data center for the integration of industry and finance, and improve the value management and risk control capabilities, so as to achieve the effect of pollution reduction and carbon reduction.

Intelligent financial architects accounted for 48.63%, ranking third, indicating that with the deep integration of artificial intelligence technology and financial work, enterprises urgently need talents who understand process architecture, can dock with external financial software and hardware suppliers, and tailor-made intelligent financial systems for the enterprise. Intelligent financial auditors accounted for 44.81%, ranked last, which may be related to the basic distribution of the respondents in the financial position, the audit position personnel less. However, with the application of artificial intelligence technology in the field of auditing, the mode of auditing work has changed, and intelligent financial auditors have been born. The demand for other intelligent financial talents accounts for only 6.01%, indicating that the four types of intelligent financial talents proposed in this paper basically cover the needs of enterprises.

4.2.2. Model setup

In order to test the risk of the application of artificial intelligence, and the impact of corporate carbon reduction and pollution reduction on the demand for intelligent financial talents, this paper constructs the following ordered Logit regression model:

$$\begin{aligned}\text{Logit}(\textit{Degree}) = {} & \alpha + \gamma_1 AI + \gamma_2 \ln SO_2 + \gamma_3 \ln CO_2 + \gamma_4 Size + \gamma_5 Growth + \gamma_6 Lev \\ & + \gamma_7 Age + \gamma_8 Board + \gamma_9 Dual + \gamma_{10} Top1 + \gamma_{11} Lnallpats + \varepsilon\end{aligned}$$

where $Degree$ is the degree of demand for smart finance talent and other variables are defined as above.

4.2.3. Logit regression analysis

Table 5 reports the results of the Logit regression model. From the regression results in columns (1)-(3), it can be seen that the regression coefficient of the application of artificial intelligence (AI) on the degree of demand for smart finance talent ($Degree$) is 0.241, which is significant at 1%, i.e., it indicates that for every unit increase in the risk of application of AI, the demand of firms for smart finance talent will increase by 0.241 units, which proves the research hypothesis 2a. The regression coefficients of enterprise pollution reduction ($\ln SO_2$) and carbon reduction ($\ln CO_2$) on the degree of demand for intelligent financial talent are 0.273 and 0.234 respectively, which are significant at 1%, i.e., it indicates that for every unit increase in pollution reduction and carbon reduction, the enterprises' demand for intelligent financial talent increases by 0.273 and 0.234 units, proving research hypothesis 2b. units, proving the research hypothesis 2b.

Table 5. Analysis of Logit regression Model results

Variable	***Degree***		
	(1)	**(2)**	**(3)**
AI	0.241***(3.01)		
$\ln SO_4$		0.273***(4.22)	
$\ln CO_4$			0.234***(3.73)
Size	0.472***(3.83)	0.345***(2.73)	0.337**(2.52)
Growth	-0.071(-0.25)	-1.212(-0.45)	-0.172(-.58)
Lev	-0.285(-0.73)	-0.221(-0.13)	0.015(0.09)
Age	0.037*(4.28)	0.101**(9.34)	0.183**(9.28)
Board	-0.001(-0.22)	0.009(0.83)	0.004(0.28)
Dual	0.028(0.38)	0.186***(7.58)	0.185**(-7.52)
*Top*1	0.009(0.04)	0.018**(9.38)	0.028***(10.42)
Lnallpats	0.029***(3.05)	0.528***(8.89)	0.189***(9.42)
Constant	8.06***(313.48)	14.509***(149.28)	19.288***(159.85)
Observations	183	183	183
Adjusted R-squared	0.804	0.885	0.841
stkcd	YES	YES	YES
year	YES	YES	YES

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

4.3. Optimization of Intelligent Financial Talent Cultivation Path

(1) Reconstructing the goal of training high-quality financial talents driven by enterprise carbon reduction and pollution reduction

Based on the core value orientation of “cultivating moral integrity” and the two strategies of “Civic and Political Leadership” and “Digital and Intelligent Empowerment”, we are committed to comprehensively reshaping the intelligent and high-quality financial talent cultivation system driven by the new quality of productivity. This system aims to promote the in-depth integration of high-quality financial talent education with ideological education and modern information technology, and to build a digital and intelligent upgraded curriculum system and ideological syllabus for high-quality financial talent training. In this process, it is necessary to develop a series of intelligent teaching materials, gold classes, cases and new liberal arts experimental platforms to provide strong support for the intelligent transformation and upgrading of the finance profession. At the same time, it is also necessary to build an intelligent faculty to meet the needs of education in the new era. Construct and implement a “industry-academia-research-creation-use” five-in-one multi-body collaborative education platform. This platform will solve practical problems through in-depth cooperation with enterprises, create three-dimensional application scenarios, and build practice teaching bases together.

(2) Establishing a training model that integrates “industry, competition and education”.

First of all, regarding the expansion of the teaching field, that is, enterprises not only exist outside the campus, but are directly integrated into the education system. This means that enterprises can not only set up laboratories and workshops on campus, but also participate in curriculum design and teaching activities. At the same time, students are no longer confined to classrooms and textbooks; they have the opportunity to go out of campus and into enterprises to combine theoretical knowledge with practical operation through internships and workshops. Secondly, promoting the deep integration of teaching and competition is an important strategy to promote teaching and learning by competition. Teachers and students should actively participate in all kinds of competitions. Through the competition platform, they can get in touch with the latest developments in the industry, which can not only stimulate their interest in learning, but also further mobilize their desire for knowledge and exploration. Finally, building a virtual simulation trial and error platform is an important direction of educational innovation. Such a platform can provide a safe environment for students so that they can try boldly and make mistakes.

(3) Re-establishing a diversified and composite new quality curriculum

The advancement of artificial intelligence technology also puts higher demands on the professional ability of accountants. To adapt to this change, accountants must acquire sufficient specialized technical knowledge and competence to continue to provide professional services and perform high-quality accounting work in future business environments. In this regard, it is necessary to add more courses related to intelligent technology on the basis of traditional accounting education, such as the “Intelligence + Finance” course system, which includes but is not limited to data mining and machine learning, IT governance and risk management, IT accounting practice, big data accounting theory and practice and other courses. Through the study of these courses, students can not only master the basic knowledge and skills in the field of data mining and machine learning, but also gain effective knowledge of IT governance and risk management, understand the practical operation of IT accounting, and learn how to use big data technology for accounting analysis.

(4) Strengthening the “Dual Supervisor” Responsibility System for Dissertations

The original intention of the “dual tutor” training model is to improve the comprehensive quality of students through the joint training of academic tutors on campus and practical tutors off campus, with a view to achieving the organic combination of theoretical knowledge and practical skills. However, in practice, this mode of training to a certain extent suffers from the problem of formalism, that is to say, the internal and external tutors do not really play their respective roles and play their due roles together. In this way, on-campus tutors can better understand the industry dynamics and improve their own industry-university-research cooperation ability, so as to more effectively guide students' academic research and career planning. Finally, it is also necessary to establish a regular communication mechanism between internal and external tutors. This mechanism can promote information sharing and resource integration between internal and external tutors, so that both sides can work better together to provide students with more comprehensive and in-depth training, and truly realize the effective collaboration between internal and external tutors and improve the quality of student training.

5. Conclusion

Under the ambitious goal of building a beautiful China, artificial intelligence is increasingly becoming a key force in promoting the synergy of carbon reduction, pollution reduction and green growth. Through the optimization of the energy system, industrial process reengineering and environmental intelligent governance, AI has shown remarkable potential in improving energy efficiency, reducing pollution, expanding ecological capacity and promoting green economic growth, laying a technological foundation for the realization of high-quality green development. At the same time, it should also be recognized that AI, as an emerging technology still under rapid development, is accompanied by many uncertainty risks in the process of empowering green transformation. In order to cope with the risks of the application of artificial intelligence, colleges and universities must update their education model, optimize teachers through school-enterprise cooperation, industry-teaching fusion, reshape curriculum standards, and innovate the professional system to achieve the in-depth fusion of education content and industry practice, ensure that the teaching content is updated in tandem with the development of technology, strengthen the students' digital literacy and professional competence, and cultivate a new type of intelligent financial talents who are both proficient in financial knowledge and mastering modern information technology. Empower enterprises to realize carbon reduction and pollution reduction.

Acknowledgements

This work was supported by the High-Quality Development Research Center of the Chengdu-Chongqing Dual-City Economic Circle (Key Research Base of Philosophy and Social Sciences in Deyang City; Grant No.: DYCY2518) and the Special Project of Tianfu College of Southwestern University of Finance and Economics (Grant No.: TFXJ2025KJXY001).

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