Cultivation Path for Innovation Ability of Sci-Tech Talents in the Background of Big Data

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Abstract—China mainly relies on higher education to cultivate sci-tech talents. The decision makers and workers of higher education face the important task of cultivating high-quality sci-tech talents that benefits the society. However, the current cultivation system for the innovation ability of high-quality sci-tech talents has some defects, and the practical experience is severely lacking for the cultivation of big data ability of high-quality sci-tech talents. Therefore, this paper explores the cultivation path for innovation ability of sci-tech talents in the background of big data. Firstly, a pre-survey was carried out on the factors affecting the innovation ability of sci-tech talents in the background of big data, an evaluation index system was established for the said ability, and the cultivation path was given for that ability. Next, the gradient boosted decision tree (GBDT) was combined with neural network (NN) into a hybrid approach, which integrates the merits of both methods. The hybrid approach was adopted to analyze and evaluate the factors affecting the innovation ability of sci-tech talents. Then, the authors further explored whether the basic ability, technology ability, and management ability of big data analysis promotes the optimization of the cultivation path for innovation ability of sci-tech talents. Through experiments, the authors obtained the regression analysis results on the innovation ability of sci-tech talents, and put forward suggestions on how to optimize the cultivation path for innovation ability of sci-tech talents.

Keywords—background of big data, sci-tech talents, innovation ability

1 Introduction

With the rapid sic-tech development around the world, the competition of comprehensive national strength is essentially a contest of sci-tech power. The sci-tech development of a country needs to be promoted by sci-tech talents [1-5]. The quality of sci-tech talents has become the main determinant of personal destiny, and even comprehensive national strength [6-8]. China mainly relies on higher education to cultivate sci-tech talents. The decision makers and workers of higher education face the important task of cultivating high-quality sci-tech talents that benefits the society [9-12]. In the age of the big data, big data analysis technologies, such as data warehouse, data security, data analysis, and data mining, are in the limelight. It is practical to analyze how the big data ability of sci-tech talents acts on the cultivation of their innovation ability, from the angle of ability composition.

In the era of knowledge economy, high and new technology industries design many incentives for sci-tech talents. Considering the problems of the incentive mechanism for sci-tech talents, Zhao [13] drew on the ideas and methodologies of human capital theory, behavioral science, and motivation theory, and constructed a brand-new incentive mechanism for sci-tech talents. The enthusiasm, initiative, and creativity of sci-tech talents can be fundamentally stimulated by combining the financial capital gain of high-tech enterprises with the ability, contribution, behavior, and effort of sci-tech talents. Through data envelopment analysis (DEA), Wang and Zhou [14] constructed a DEA model with human resource and financial resource as the inputs, and knowledge output, economic benefit, and social benefit as the outputs, according to the features of local industry development, as well as the status quo of high-level sci-tech talent team.

With the dawn of the age of artificial intelligence and big data, it is more and more important to cultivate information talents. Colleges need to reform curriculum, and adjust cultivation goals, in order to cultivate applied information talents, who master artificial intelligence and big data. Focusing on the reform of the corporate resource planning course, Wang and Guan [15] expounded on the cultivation of information talents from the perspective of the course, fully analyzed the current situation and existing problems of the course teaching, and adopted the basic ideas of blended education and teaching to give full play to the advantages of traditional and online learning modes.

Taking Ordos Institute of Technology for example, Ma et al. [16] devised a professional talent cultivation system for data science and big data technology, through a discussion on six issues: talent cultivation goals, curriculum structure, faculty construction, teaching research and reform, practical teaching, and school-enterprise cooperation. Their research provides a reference for undergraduate colleges to reform and develop big data professionals. Guo and Wang [17] modeled the factors affecting the autonomous innovation of college sci-tech talents, analyzed the mechanism of innovation organization acting on innovation ability, and summarized how innovation ability affects innovation results: innovation organization affects innovation results via the innovation ability.

In China, the current cultivation system for the innovation ability of high-quality sci-tech talents has some defects: the cultivation contents are outdated, the talents are not divided into clear layers, heuristic innovative teaching is rare, and some key links of cultivation are missing (e.g., active thinking of innovation talents, and the expansion of innovative thinking). As a result, the cultivation of the innovation ability of sci-tech talents cannot fully satisfy the needs to improve sci-tech power. Besides, the practical experience is severely lacking for the cultivation of big data ability of high-quality sci-tech talents. The applied research of data mining, data screening, and other big data analysis techniques mainly concentrate on the macro-level, which is the mainstream direction of big data research.

This paper explores the cultivation path for innovation ability of sci-tech talents in the background of big data. The main contents are as follows: Section 2 pre-surveys the factors affecting the innovation ability of sci-tech talents in the background of big data, formulates an evaluation index system for the said ability, and provides the cultivation path for that ability. Section 3 combines the gradient boosted decision tree (GBDT) with neural network (NN) into a hybrid approach, which integrates the merits of both methods. The hybrid approach was adopted to analyze and evaluate the factors affecting the innovation ability of sci-tech talents. Section 4 further explores whether the basic ability, technology ability, and management ability of big data analysis promotes the optimization of the cultivation path for innovation ability of sci-tech talents. Section 5 offers the regression analysis results on the innovation ability of sci-tech talents, and puts forward suggestions on how to optimize the cultivation path for innovation ability of sci-tech talents.

2 Cultivation path analysis

To realize accurate and scientific cultivation of the innovation ability of sci-tech talents, it is necessary to pre-survey the factors affecting the innovation ability of sci-tech talents in the background of big data, and formulate an evaluation index system for the said ability (Figure 1).

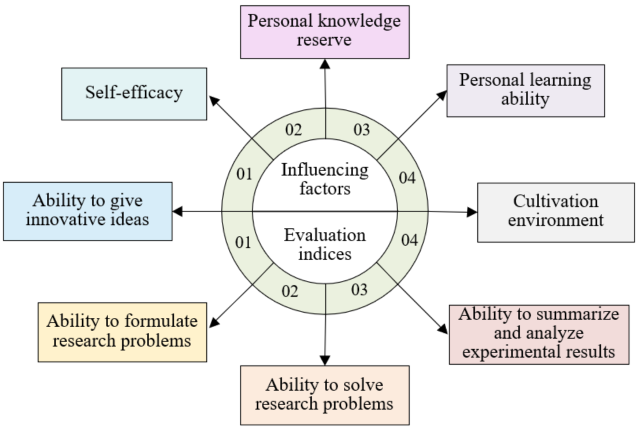


Fig. 1. Influencing factors and evaluation indices

In the background of big data, the innovation ability of sci-tech talents is affected by four different factors, including the self-efficacy, personal knowledge reserve, personal learning ability, and cultivation environment of sci-tech talents.

Specifically, self-efficacy covers three aspects: the confidence to solve general and sudden engineering problems, the persistent pursuit of ideals and effort making, and the calmness to cope with troubles and difficulties.

Personal knowledge reserve covers four aspects: the mastery of systematic theoretical knowledge, the knowledge of professional hot topics, the grasp of relevant knowledge in other disciplines, and the ability to use relevant basic knowledge of other disciplines.

Personal learning ability covers eight aspects: the basic ability of big data analysis, the technology ability of big data analysis, the management ability of big data analysis, the proficiency of big data analysis software, the proficiency of scientific experimental instruments, the ability to build theoretical models for research problems, the ability to view problems dialectically, and the ability to theoretically analyze experimental results.

Cultivation environment covers seven aspects: the innovation spirit of surrounding teachers and students, the strong research ability of the tutor, frequent teacher-student interactions, good research conditions, good research atmosphere, reasonable cultivation plan, and availability of online learning platform.

In the background of big data, the innovation ability of sci-tech talents can be evaluated by four primary indices, including the ability to give innovative ideas, the ability to formulate research problems, the ability to solve research problems, and the ability to summarize and analyze experimental results.

Specifically, the ability to give innovative ideas consists of four secondary indices: the ability to look up relevant literature, the ability to raise innovative views, the ability to work collaboratively, and the ability to communicate research ideas.

The ability to formulate research problems consists of four secondary indices: the ability to review the theoretical research, the ability to read the literature, the ability to determine the research direction, and the ability to write a good paper.

The ability to solve research problems consists of three secondary indices: the ability to collect data through big data analysis, the ability to carry out experiments, and the ability to operate big data analysis software.

The ability to summarize and analyze experimental results consists of the following secondary indices: the ability to summarize research data, the ability to analyze research data through big data analysis, the ability to analyze and explain the research conclusions, and the ability to defend and write out the research ideas.

Figure 2 explains the cultivation path for innovation ability of sci-tech talents in the background of big data. It can be observed that, in the background of big data, the innovation ability of sci-tech talents is improved through a spiral path of innovative research and development: giving innovative ideas→formulating research problems→solving research problems→summarizing and analyzing experimental results. However, the basic ability of big data analysis, technology ability of big data analysis, and management ability of big data analysis, are not acquired at the same time. In fact, these abilities are acquired through the analysis of different big data, enabling sci-tech talents to accumulate knowledge and technology innovation.

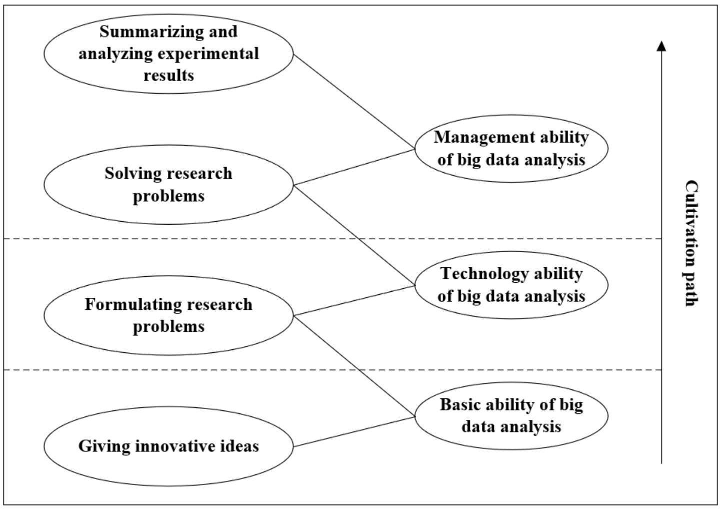


Fig. 2. Cultivation path

3 Innovation ability evaluation

Compared with simple decision tree learners, the GBDT model makes accurate predictions, and minimizes the prediction offset, using the square sum of exponential sums. The NN operation consumes a long time, owing to the iterative adjustment of model parameters. This paper combines the merits of GBDT with NN to analyze and evaluate the factors affecting the innovation ability of sci-tech talents. Figure 3 explains the flow of GBDT.

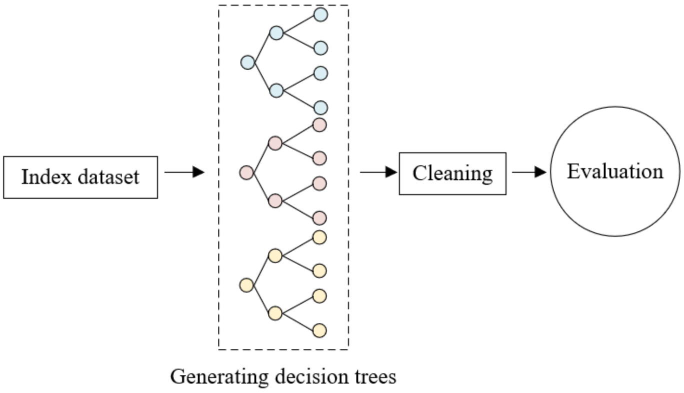


Fig. 3. Flow of GBDT

In the analysis model for the influencing factors, the explained variable (innovation ability of sci-tech talents) B is equal to 0 or 1. The explanatory variables A corresponding to the influencing factors (self-efficacy, personal knowledge reserve, personal learning ability, and cultivation environment) are assigned real data. This paper constructs a logistic regression model to monitor the values of the above variables. Let $q \in R^m$ and $\varphi \in R$ be the weighted vector and bias, respectively; $q \cdot a$ be the inner product between Q and A. The conditional probabilities can be expressed as:

$$RL\left(B=1|a\right)=\frac{exp\left(q\cdot a+\phi\right)}{1+exp\left(q\cdot a+\phi\right)} \tag{1}$$

$$RL\left(B=1|a\right)=\frac{1}{1+exp\left(q\cdot a+\phi\right)} \tag{2}$$

Concerning the value of explained variable a, the probabilities $RL(B=1|a)$ and $RL(B=0|a)$ for the analysis on the factors affecting the innovation ability of sci-tech talents can be solved by formulas (1) and (2). Comparing $RL(B=1|a)$ with $RL(B=0|a)$, the Sigmoid-based explanatory variable a can be allocated by the logistic regression model to the class with the larger conditional probability.

The GBDT model needs to go through three steps (feature selection, decision tree generation, and cleaning) before forming the final decision. The input is the evaluation index dataset for the innovation ability of sci-tech talents; the loss function is the $SU(b,g(a))$; the output is the regression tree $g(a)$. The model is implemented in the following steps:

The model can be initialized as:

$$g_0\left(a\right)=argmin\sum_{i=1}^{M}SU\left(b_i,z\right) \tag{3}$$

For i=1,2,...,M, we have:

$$s_{ni}=-\left[\frac{\partial SU\left(b_i,g\left(a_i\right)\right)}{\partial g\left(a_i\right)}\right]_{g(a)=g_{n-1}(a)} \tag{4}$$

Based on s_{ni} in formula (4), the regression tree is fitted. Let S_{nj} be the leaf node area of the n-th tree. For j=1,2,3,...,j, we have:

$$z_{nj}=argmin\sum_{a_i\in R_{nj}}SU\left(b_i,g_{n-1}\left(a_i\right)+z\right) \tag{5}$$

The regression tree can be updated by:

$$g_n\left(a\right)=g_{n-1}\left(a\right)+\sum_{n=1}^{N}PV\left(a\in R_{nj}\right) \tag{6}$$

The regression tree can be finalized as:

$$\hat{g}\left(a\right)=g_N\left(a\right)=\sum_{n=1}^{N}\sum_{j=1}^{OF}z_{mj}PV\left(a\in R_{nj}\right) \tag{7}$$

In the adopted backpropagation neural network (BPNN), two types of information are propagating forward, and propagating backward layer by layer, respectively. The former is outputted by the output layer, carrying the information about input and weights. The latter is the error between theoretical and actual values. In our BPNN, the input layer receives the eigenvectors of the evaluation index data: $A=[a_1,a_2,...,a_m]$.

Let θ_1 and G_1 be the weight vector and activation function of the first hidden layer, respectively. In the BPNN, the hidden layer firstly solves the weighted sum of the index data of the input layer. Then, the result is processed by the activation function $P_1=G_1(A\theta_1)$. The hidden layer adopts the *Sigmoid* as the activation function. Then, we have:

$$g(a)=\frac{1}{1+e^{-\beta a}}\left(0<g(a)<1\right) \tag{8}$$

The output layer can be solved by:

$$P_2=G_2\left(G_1\left(A\theta_1\right)\theta_2\right) \tag{9}$$

Let $\Delta\theta_{jl}=-\delta\partial S/\partial\theta_{jl}$; $\Phi_l=-(d_l-P_l)P_l(1-P_l)$ be the error. If the output error of the BPNN does not reach the preset error, the network weights need to be adjusted to reduce the mean squared error of the NN: $S=1/2U\sum_U\sum_A(d_{ul}-P_{ul})^2$. Then, we have:

$$\theta_{jl}\left(d+1\right)=\theta_{jl}\left(d\right)+\Delta\theta_{jl} \tag{10}$$

Let $\Delta\theta_{ij}=-\delta\partial S/\partial\theta_{ij}$; $\Phi_j=\sum_l\Phi_l\theta_{jl}P_j(1-P_j)P_j$ be the error. After adjusting the weights of the output layer and the hidden layer, the error of the NN will propagate backward to further optimize network output. The backpropagation can be illustrated by:

$$\theta_{ij}\left(d+1\right)=\theta_{ij}\left(d\right)+\Delta\theta_{ij} \tag{11}$$

4 Cultivation path optimization

Further discussion is needed to verify whether the basic ability, technology ability, and management ability can promote the cultivation path for innovation ability of sci-tech talents. In the background of the big data, the clustering of the cultivation elements for the innovation ability of sci-tech talents was associated with the cultivation space to build a spatial econometric model for the cultivation of the innovation ability of sci-tech talents. The model was adopted to analyze the influence of the development level of big data analysis technology over the optimization of the cultivation path for innovation ability of sci-tech talents, as well as the spatial spillover effect of the cultivation space. The purpose is to effectively optimize the cultivation path.

Let i be the serial number of regions; d be the serial number of periods; *PWOQ* be the reasonability of the cultivation path; $PWOQ_{id\text{-}1}$ be the lag term of PWOQ; SJ be the development level of big data analysis technology (explanatory variable); AC be the control variable; λ be the regional difference; σ be the disturbance term; β_1, β_2, and

α_i be the parameters to be estimated for the variables. Following the principle of theoretical analysis on dynamic data panel model, this paper proposes the following optimization model of the cultivation path for innovation ability of sci-tech talents:

$$PWOQ_{id} = \beta_1 PWOQ_{id-1} + \beta_2 SJ_{id} + \sum_1^m \alpha_i A_{id} + \delta_i + \lambda_i + \sigma_{id} \tag{12}$$

Before the regression analysis on the spatial econometric model, it is necessary to judge whether the cultivation elements for the innovation ability of sci-tech talents in each region cluster in space. Let M be the total number of regions being studied; θ_{ij} be the spatial weights of regions i and j, respectively; r_i and r_j be the observations of the variables in regions i and j, respectively; r^* be the mean observation. The matrix constructed based on θ_{ij} is symmetric. This paper measures the spatial autocorrelation of the cultivation elements in each region with the Global Moran's I index:

$$OSMI = \frac{M\sum_{i=1}^{M}\sum_{j=1}^{M}\theta_{ij}\left(r_i - r^*\right)\left(r_j - r^*\right)}{\sum_{i=I}^{M}\left(r_i - r^*\right)^2 \sum_{i=1}^{M}\sum_{j=1}^{M}\theta_{ij}} \tag{13}$$

The Local Moran's I index can be calculated by:

$$LMI_i = \frac{\left(r_i - r^*\right)\sum_{j\neq i}^{M}\theta_{ij}\left(r_j - r^*\right)}{E^2\sum_{i=1}^{M}\sum_{j=1}^{M}\theta_{ij}} \tag{14}$$

Next, a suitable expression was constructed for the spatial econometric model of the innovation ability of sci-tech talents, aiming to effectively analyze the influence of the development level of big data analysis technology over the optimization of the cultivation path for innovation ability of sci-tech talents, as well as the spatial spillover effect of the cultivation space. Let ψ be a constant term; ε and ϕ be the parameters to be estimated; ω be the spatial weight matrix; η_i be the fixed effects; u_d be the random effects; ρ_{id} be the error term, which depends on the spatial lagging error $\omega\rho_{id}$ and random error σ_{id}. Then, the spatial lag model, spatial error model, and spatial Durbin model can be respectively expressed as:

$$\begin{aligned} &PWOQ_{id} = \psi + \varepsilon\omega PWOQ_{id} + \varphi_1 SJ_{id} + \varphi_2 \ln GAK_{id} \\ &+\varphi_3 MO_{id} + \varphi_4 FY_{id} + \varphi_5 HX_{id} + \eta_i + u_d + \sigma_{id} \end{aligned} \tag{15}$$

$$\begin{aligned} &PWOQ_{id} = \beta + \alpha_1 SJ_{it} + \alpha_2 \ln GAK_{id} + \alpha_3 MO_{id} + \alpha_4 FY_{id} + \alpha_5 HX_{it} + \eta_i + u_d + \rho_{id} \\ &\rho_{id} = \Psi\theta\rho_{id} + \sigma_{id} \end{aligned} \tag{16}$$

$$\begin{aligned} &PWOQ_{id} = \beta + \varepsilon\theta PWOQ_{id} + \alpha_1 SJ_{id} + \alpha_2 \ln JAK_{id} + \alpha_3 MO_{id} + \alpha_4 FY_{id} \\ &+\alpha_5 HX_{id} + \alpha_6\theta SJ_{id} + \alpha_7\theta \ln JAK_{id} + \alpha_8\theta MO_{id} + \alpha_9\theta HX_{id} + \eta_i + u_d + \rho_{id} \end{aligned} \tag{17}$$

The analysis results directly depend on the spatial weight matrix, which characterizes the degree of spatial association. Three kinds of spatial weight matrices are involved here: the adjacency weight matrix of the cultivation space for the innovation ability of sci-tech talents; the geographical distance weight matrix of the cultivation space; the development level distance weight matrix of the big data analysis technology. The elements in the adjacency weight matrix are assigned, according to whether the cultivation space units are adjacent to each other:

$$q_{ij}=\begin{cases}1, if\ \ spatial\ units\ i\ and\ j\ are\ adjacent\ to\ each\ other\\0, otherwise\end{cases} \tag{18}$$

Let Ω_{ij} be the distance from the center of unit i to that of unit j. Then, the elements in the geographical distance weight matrix are assigned, according to the geographical distance between the cultivation space units:

$$q_{ij}=\begin{cases}\dfrac{1}{\Omega_{ij}^{2}}, i\neq j\\0, i=j\end{cases} \tag{19}$$

Let KZS_i and KZS_j be the scores of big data analysis ability of talents in regions i and j, respectively. Then, the elements in the development level distance weight matrix are assigned, according to the development level of big data analysis technology between regions:

$$q_{ij}=\begin{cases}\dfrac{1}{\left|KZS_i-KZS_j\right|}, i\neq j\\0, i=j\end{cases} \tag{20}$$

5 Experiments and results analysis

To optimize the structure of our NN, the number of nodes in each layer was determined through tests. Figure 4 reports the test results with different number of nodes. With the growing number of nodes, the area under the curve (AUC) tended to be stable in different test ranges of the samples. That is, the positive samples obtained higher scores than negative ones.

Table 1 presents the regression analysis results on the innovation ability of sci-tech talents. It can be seen that the four influencing factors, namely, self-efficacy, personal knowledge reserve, personal learning ability, and cultivation environment, did not significantly influence the four indices: the ability to give innovative ideas, the ability to formulate research problems, the ability to solve research problems, and the ability to summarize and analyze experimental results.

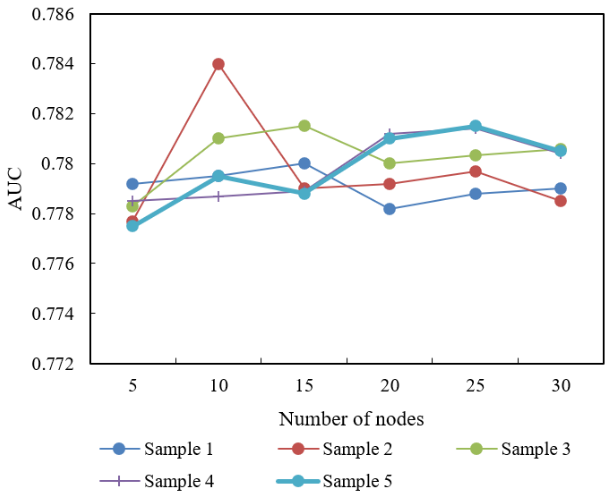


Fig. 4. AUCs of different samples

Table 1. Regression analysis on innovation ability of sci-tech talents

Variable	The ability to give innovative ideas		The ability to formulate research problems	
	Model 1	***Model 2***	***Model 1***	***Model 2***
Self-efficacy	-0.251**	-0.048	-0.052	-0.08
Personal knowledge reserve	0.037	0.016	0.025	0.016
Personal learning ability	0.062	0.085	0.069	0.058
Cultivation environment	0.018	-0.027	0.081	-0.045
Basic ability of big data analysis	/	0.362***	/	0.452**
Technology ability of big data analysis	/	0.458***	/	0.408***
Management ability of big data analysis	/	0.105	/	0.185
R^2	0.031	0.418	0.018	0.852
ΔR^2	0.048	0.462	0.041	0.694
F	1.7	42.182***	1.629**	46.28***
Variable	**The ability to solve research problems**		**The ability to summarize and analyze experimental results**	
	Model 1	***Model 2***	***Model 1***	***Model 2***
Self-efficacy	-0.152	-0.019	-0.162**	-0.145**
Personal knowledge reserve	-0.048	-0.035	-0.482	-0.013
Personal learning ability	-0.057	-0.048	-0.163	-0.017
Cultivation environment	0.326	0.039	0.326***	0.026
Basic ability of big data analysis	/	0.548**	/	0.528**
Technology ability of big data analysis	/	0.374**	/	0..484**
Management ability of big data analysis	/	0.092	/	0.063
R^2	0.05	0.745	0.472	0.592
ΔR^2	0.069	0.628	0.436	0.505
F	5.485***	57.162***	53.16**	55.417***

According to the results on the proposed NN (Model 2), in terms of the sci-tech talents' ability to give innovative ideas, the r values of the basic ability of big data analysis, and technology ability of big data analysis were 0.362 and 0.458, respectively ($p<0.001$). Thus, these two indices significantly promote the innovation ability. The r value of the management ability of big data analysis was 0.105 ($p>0.005$), i.e., this index does not significantly affect the innovation ability.

In terms of the sci-tech talents' ability to formulate research problems, the r values of the basic ability of big data analysis, and technology ability of big data analysis were 0.452 and 0.408, respectively ($p<0.001$). Thus, these two indices significantly promote the innovation ability. The r value of the management ability of big data analysis was 0.185 ($p>0.005$), i.e., this index does not significantly affect the innovation ability.

In terms of the sci-tech talents' ability to solve research problems, the r values of the basic ability of big data analysis, and technology ability of big data analysis were 0.548 and 0.374, respectively ($p<0.001$). Thus, these two indices significantly promote the innovation ability. The r value of the management ability of big data analysis was 0.092 ($p>0.05$), i.e., this index does not significantly affect the innovation ability.

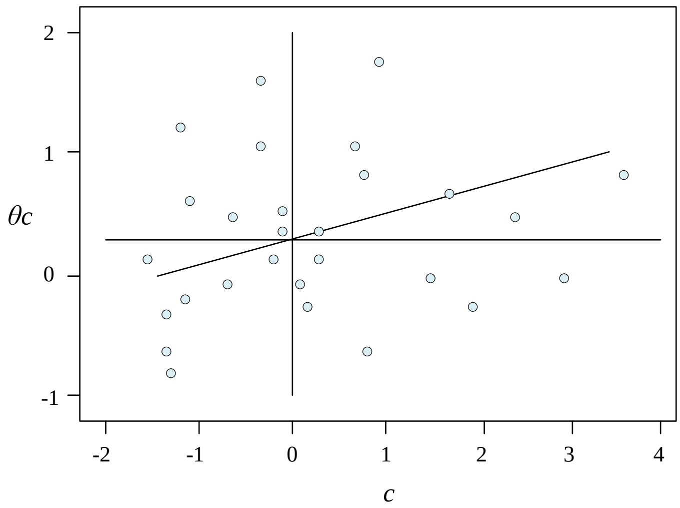
In terms of the sci-tech talents' ability to summarize and analyze experimental results, the r values of the basic ability of big data analysis, and technology ability of big data analysis were 0.528 and 0.484, respectively ($p<0.001$). Thus, these two indices significantly promote the innovation ability. The r value of the management ability of big data analysis was 0.063 ($p>0.005$), i.e., this index does not significantly affect the innovation ability.

In addition, all variables were quantized to alleviate the oscillation of the data on the influencing factors, and reduce the possible heteroscedasticity of the two proposed models. Table 2 lists the descriptive statistics of seven influencing factors.

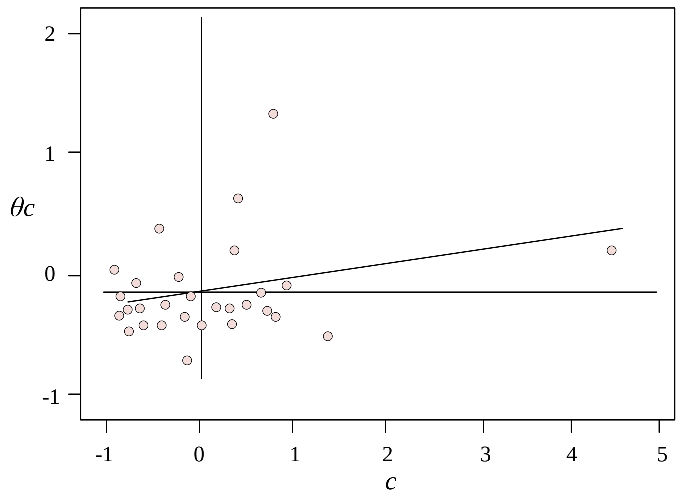
Table 2. Descriptive statistics of influencing factors

Name	Mean	Standard deviation	Minimum	Maximum	Number of samples
Self-efficacy	0.3268	0.1824	0.0528	0.7925	251
Personal knowledge reserve	0.1427	0.1562	0.0639	0.9582	236
Personal learning ability	0.1925	0.1474	0.0125	0.7185	205
Cultivation environment	8.1742	1.6295	5.0674	12.6395	214
Basic ability of big data analysis	0.5293	0.2518	0.3925	0.7419	236
Technology ability of big data analysis	9.4712	0.8472	7.4851	13.2620	208
Management ability of big data analysis	0.2693	0.1362	0.2518	0.7416	220

To further analyze the local space autocorrelation for the cultivation path optimization between each region and the adjacent regions, the Global and Local Moran's I scatterplots (Figure 5) were drawn for the reasonability of the cultivation elements in 25 studied regions. It can be seen that more regions clustered in quadrants 1 and 3 than quadrants 2 and 4. Hence, the optimization levels of the different regions are mainly distributed in the form of high-high clustering and low-low clustering.



(1) Scatterplot of Global Moran's I



(2) Scatterplot of Local Moran's I

Fig. 5. Scatterplots of Global and Local Moran's I

6 Conclusions

This paper mainly investigates the cultivation path for innovation ability of sci-tech talents in the background of big data. Specifically, the factors affecting the innovation ability of sci-tech talents in the background of big data were pre-surveyed, an evaluation index system was established for the said ability, and the cultivation path of that ability was clarified in the background of big data. Next, the influencing factors were analyzed and evaluated by GBDT and NN. Further research was carried out to verify if the basic ability, technology ability, and management ability of big data analysis promotes the optimization of the cultivation path for innovation ability of sci-tech talents. Through experiments, the number of nodes was determined for each layer of our NN, the descriptive statistics of 7 influencing factors were obtained, and the Global and Local Moran's I scatterplots were drawn. It was concluded that the optimization levels of the different regions are mainly distributed in the form of high-high clustering and low-low clustering.

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