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Forecast of Advanced Human Capital Gap Based on PSO-BP Neural Network and Coordination Pathway: Example of Beijing–Tianjin–Hebei Region

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Abstract: The upgrading of human capital caused by education is significant to regional development. Reasonable predictions of the degree of advanced human capital in different regions are effective for formulating reasonable talent policies and accelerating regional coordinated development. The BP neural network is a widely used prediction technology. PSO-BP neural network has good global search ability, which can accelerate the convergence speed of traditional BP neural network, which is suitable for forecasting larger data. The study takes the provincial data of China from 2005 to 2019 as an example, using PSO-BP neural network algorithm to predict the advanced level of human capital through the influencing factors filtered by OLS regression. The results show that: (1) Innovation ability and urbanization can play a decisive role in advanced human capital filtered by OLS regression; (2) The results of predicting the development trend of advanced human capital in the Beijing–Tianjin–Hebei region in 2020–2025 through the PSO-BP neural network have showed that there is still a large gap between the senior human capital stock in Hebei-Beijing-Tianjin in terms of total and per capita in 2020–2025 compared with other regions in east of China; (3) Giving full attention to elaborate the positive role of economic quality and quantity development are suitable for narrowing the difference of advanced human capital in this region. Through the method of OLS-BP-neural network, this study explores the gap and influencing factors of the Beijing–Tianjin–Hebei region, excavates the reasons for the huge gradient difference in the development of this region, and extends the machine learning prediction method to the analysis of the advanced level of human capital and the research of narrowing the regional development gap.

Keywords: supervised learning; PSO-BP neural network; advanced human capital level forecast; Beijing–Tianjin–Hebei region coordination

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1. Introduction

1.1. Background

With the push to coordinate the regional development in a low-carbon and green development model, some regions in China, such as Yangtze River Delta region, have been created as green and low-carbon development sample areas (Chen et al., 2001) [1]. Since the plan of "Green and Low-carbon Integration Demonstration Zone Construction Plan in the Yangtze River Delta" is released (Zhen et al., 2022) [2], a new mechanism of connected four coordinated elements industrial development, coordinated environmental governance, coordinated ecological protection, and coordinated utilization of resources is explored. In these mechanisms, the coordinated industrial development is quite important for a low-carbon and green development model. People are the first productive force for any society (Beyer, 2016) [3]. Nowadays, advanced human capital raised by higher education is significantly affected by the industry development from the industrial input end (Janice et al., 1992) [4], so it is of great importance to obtain a clear concept of human capital's function, especially its role in regional development. Beijing–Tianjin–Hebei region is the most important urban agglomeration area in northern China, and it not only has a significant effect on the northern politics, economy, and culture but also have significant effects on the balanced development for the north and the south of China. In addition, promoting the coordinated development of the Beijing–Tianjin–Hebei region is a major national strategy in China.

The Beijing–Tianjin–Hebei region has the characteristic of geographical connectedness, culturally alike and a sound economic foundation. In addition, its labor exchanges are frequent. After the reform and opening up, the three local governments have been striving to achieve complementary benefits and a win-win development model with coordination and a cooperation plan (Yuan et al., 2020) [5]. The "Beijing-Tianjin-Tangshan" regional development plan in the 1980s was the first coordination and cooperation plan for this area; known then as the "Bohai Rim Economic Circle", it was put forward in the 1990s. In 2014, the "Beijing-Tianjin-Hebei Regional coordination" plan and the "Capital Economic Circle" plan were brought forward to further push the blueprint into reality. Although there are sustained plans to push, it is difficult to have a true meaning for breaking through. The reasons are due to the influence of GDP achievements for local government, the trend of a homogeneous industrial structure that affects the enterprises' cooperation. One more important reason is that Beijing, as the core city in this region, receives a better service industry rather than manufacturing industry with a long industrial chain which is dissimilar to the Yangtze River Delta and Guangdong–Hong Kong–Macao Greater Bay Area, (Deng, 2019) [6]. Thus, there exists a more "siphon effect" than "radiation effect" for its surrounding areas (Wu et al., 2019) [7].

Like the Yangtze River Delta region, the Beijing–Tianjin–Hebei region can shape regional comparative advantages and follow low-carbon and green development requirements to obtain regional industry upgrade, especially for the non-capital function diversion and regional coordination break through. In addition, advanced human capital is a quite important influencing factor. The higher education resources endowment in Beijing–Tianjin–Hebei region is in leading status in China; however, compared with the Yangtze River Delta and Guangdong–Hong Kong–Macao Greater Bay Area, the human capital does not have a comparative advantage. In 2019, a "world-class innovation platform and growth pole" was put forward in the Central Working Conference which involves Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Guangdong–Hong Kong–Macao Greater Bay Area. In 2019, the college degree or above on population in Beijing–Tianjin–Hebei was 1.29850 million, in the Yangtze River Delta was 3.49790 million, and in Guangdong–Hong Kong–Macao Greater Bay Area was 2.06770 million. Obviously, compared with the central cities in the Yangtze River Delta and Guangdong–Hong Kong–Macao Greater Bay Area, there is still a significant quantitative gap in the level of senior human capital in the Beijing–Tianjin–Hebei area. From the school cultivation perspective, in 2020, the ordinary undergraduate and junior college students amount in major cities in Beijing–Tianjin–Hebei area are Beijing 0.60887 million, Tianjin 0.57215 million, Shijiazhuang 0.58347 million, in Yangtze River Delta is Shanghai 0.54069 million, Nanjing 0.91814 million, Hangzhou 0.46596 million, Hefei 0.58617 million, and in Guangdong–Hong Kong–Macao Greater Bay Area is Guangzhou 2.4002 million, and Shenzhen 0.10999 million. Which means in 2020, in the Beijing–Tianjin–Hebei area, the total number of students is 2.0556 million, in the Yangtze River Delta is 3.7344 million, and in Guangdong–Hong Kong–Macao Greater Bay Area is 2.4002 million. Thus, there is a big potential advantage in the Beijing–Tianjin–Hebei area. Given the critical role of higher education in the process of human capital formation (Kamalika et al., 2018) [8], and the spillover effect of human capital itself (Ortiz et al., 2022) [9], how to obtain a better understanding about the structure and trend of human capital development in Beijing–Tianjin–Hebei area so as to bring out the potentials of advanced human capital in this area is an important issue in regional coordinated development. In addition, starting from the increase in senior human capital stock to obtain continuous upgrading of human capital structure so as to fulfill the need for coordination of regional industrial development is a rational breakthrough strategy.

This study is trying to answer the problem of whether there is a human capital resource obstacle for Beijing–Tianjin–Hebei coordinated development, and how to deal with the obstacle so as to narrow the gap and meet the industry upgrade and low-carbon development model requirements. Due to the economic and social differences especially industry differences, to the narrow gap in this region, there should be forecast a trend from a future view according to the current situation. The prediction method of backpropagation (BP) neural network has a characteristic of not according to detailed material constitutive parameters (Chen et al., 2020) [10] and it has a good feature of assessment data processing speed and also assessment results accuracy (Liu et al., 2022) [11]. In addition, it has a good compatibility with other methods of influencing factors screening.

Compared to existing studies, this paper's novelty features and possible marginal contributions are as follows. Firstly, using a theoretical mechanism to obtain the advanced human capital influence factor from two levels: economic development and industry adjustment progress based on the C–D production function. Secondly, a new method to predict the advanced stock of human capital is summarized. Its prediction advantage is illustrated compared with traditional single independent variable prediction. Thirdly, it can be found there is quite a difference between Beijing–Tianjin–Hebei region and other two eastern urban agglomeration, Yangtze River delta region and the Guangdong–Hong Kong–Macao Greater Bay Area. In addition, the remaining two regions obtain less advanced manpower level gaps. So, it is of great importance to put forward the strategy by enhancing the radiation effect of industry, thumb a lift to improve the overall labor quality, and to form human capital quality dividend to meet economic and social development so as to meet the needs of regional long-term stability and prosperity for Beijing–Tianjin–Hebei region.

1.2. Literature Review and Theoretical Mechanism

1.2.1. Role of Advanced Human Capital in Economy and Society

Advanced human capital is of great importance to the modern economy. From the point of industry performance, human capital can be seen as a ladder for enhancing shareholder value creation (Cecilia et al., 2017) [12]. In addition, it is also important for green total productivity (Wang et al., 2021) [13]. As an important factor of production, human capital can provide a lasting and stable power for economic development (Lucas, 1988; He, 2022) [14,15]. On the one hand, human capital directly promotes economic development by entering the production function, which can improve the labor productivity of unit labor; on the other hand, human capital can also improve the labor productivity indirectly through the "technology" variable acting in the production function (Cinnirella et al., 2017) [16], to achieve self-accumulation. Different from other factors of production, human capital will not be lost in the process of "use". Still, it can be continuously improved and accumulated through the integration with industrial development, such as "learning by doing" and enterprise training, to form a changing trend of continuous "advanced" (Alain et al., 2020) [17]. The upgrading of the human capital structure is of great significance to China's current development: it can not only make up for the depreciation of human capital caused by aging and the decline of demographic dividends by tapping the demographic quality dividend (Fu, 2018; Liu et al., 2020) [18,19]. Moreover, it can also promote the upgrading of technical structure and industrial structure (Wang et al., 2022) [20].

1.2.2. Role of Advanced Human Capital in Regional Coordinated Development

For adjusting industrial structure, breaking down the administrative barriers, improving the regional governance system are the main points found by scholar (Bian et al., 2020) [21]. There is the same situation in China for coordinated development of the Beijing–Tianjin–Hebei region (Wang et al., 2020) [22]. When the human capital level reaches a certain threshold value, the impact of environmental regulation on green technology innovation shifts significantly (Liang et al., 2023) [23]. For the human capital, due to the historical starting point of development, resource endowment and other reasons, the distribution and role of human capital in the Beijing–Tianjin–Hebei region are heterogeneous (Wu, 2018) [24]. The heterogeneity of human capital in these regions is also one of the important reasons for the development differences in the Beijing–Tianjin–Hebei region. There are quite important issues that influence regional human capital (Xiao et al., 2022) [25]. Such as the level of economic development, industrial structure, business environment (You et al., 2021) [26], innovation level, government education investment, quality of basic education (Zhao et al., 2021) [27], and medical and health level will have a significant positive role in promoting regional human capital (Mao et al., 2022) [28]. Research from the perspective of heterogeneous human capital has showed that the level of economic development and science and technology are the main factors driving the distribution of scientific and technological talents in Beijing–Tianjin–Hebei (Liu et al., 2018) [29]. Regarding the forecast of human capital demand, research based on GDP and material capital stock for forecasting (Hu et al., 2007) [30], economic growth rate, material capital growth rate, the contribution rate of total factor productivity (Guo et al., 2014) [31], years of education (Xie, 2020) [32], and so on are used to forecast China's human capital demands.

According to the existing literature, human capital has played a very important role in whole economic and society development, especially in modern regional development. On the one hand, from the production end, human capital is a quite important input factor. For modern industry development, advanced human capital plays an important role. On the other hand, economic factors from macro to micro are the main factors that influence human capital choices. However, for regional development, the macro point is quite important for coordinate policy formulation. Thus, according to the demand of Beijing–Tianjin–Hebei higher coordinated development, it is necessary to find out whether macro-economic factors have influence on advanced human capital and also it is necessary to find out whether there is a quite big advanced human capital stock gap influenced sustainable development which blocks the regional synergy.

C–D production function (Cobb–Douglas production function) can be used to analyze the relationship between input factors which affect total output, and is proved quite effective for economic effect analysis (Aigner et al., 1977; Charnes et al., 1978; Yuan et al., 2022; Liu et al., 2021) [33–36]. Due to the topic is discussing advanced human capital structural optimization demand, it should be introduced advanced human capital to represent labor force structural optimization. Following the concept of (Orazio et al., 2020) [37], the adjusted C–D production function is showed in Equation (1):

$$GDP = A \cdot K^{\alpha} \cdot HHC^{\beta} \tag{1}$$

Then refer to the endogenous growth theory (Cvetanović et al., 2015) [38], by logarithmic processing, its log form is shown in Equation (2).

$$lnGDP = lnA + \alpha \cdot lnK + \beta \cdot lnHHC \tag{2}$$

In the Equation (2), GDP represents the total output, A represents the technical level, and K represents the capital stock, which can be divided into material capital stock CS and technical capital stock PL, α and β are estimate coefficients for K and HHC, respectively. For the forecast of advanced human capital, the Equation (2) is processed as following form of Equation (3):

$$lnHHC = \frac{1}{\beta} lnGDP - \frac{\alpha}{\beta} + lnK + \frac{1}{\beta} A \tag{3}$$

Due to there is a quite difference effect of tech and capital for HHC, the effect estimate coefficients should be estimated respectively. The material capital stock (CS) represents K

and the number of patents (PL) represents A, and Equation (3) can be further written as Equation (4):

$$lnHHC = \frac{1}{\beta}lnGDP - \frac{\alpha_1}{\beta}lnCS + \frac{1}{\beta}lnPL \quad (4)$$

Considering urbanization plays an important role in human capital agglomeration (Alok et al., 2012; Zahoor et al., 2022) [39,40], the urbanization rate is also included in the prediction model, and then obtained the final prediction model of Equation (5) which can be named as Model 1.

$$lnHHC = \frac{1}{\beta}lnGDP - \frac{\alpha_1}{\beta}lnCS + \frac{1}{\beta}lnPL + \gamma lnUR \quad (5)$$

According to Model 1, the influence mechanism of advanced human capital can be analyzed from the total amount of economic growth view. Based on endogenous growth theory, the driving force of economic growth includes human capital (Cinnirella, 2017) [16], innovation (Mohamed, 2022) [41] and investment in knowledge (Romer, 1986) [42]. This indicates that the knowledge (experience) can be regarded as the output of the investment. In addition, due to connection and regional division, regions which are independent economic output sectors can generate input–output correlation through resource flows. This means talent flow and knowledge gathering have certain spillover effects (Guo et al., 2014) [31]. Because there are differences in resources allocation and industry connection, the spillover effect of knowledge has quiet difference among regions which will affect different regions high-level human capital formation. Therefore, Hypothesis 1 is proposed:

Hypothesis 1. *Regional economic growth, technology level improvement and urbanization promotion will boost the demand for advanced human capital.*

In addition, in order to verify and contrast the prediction results, and due to the GDP accounting method is given by production method, adopt industrial structure measurement to replace economic aggregate as output is reasonable. Therefore, this paper improved industrial structure advanced measurement method (Table 1) uses the advanced industrial structure (ALS) substitute for GDP of Equation (5). In addition, because of the basis of advanced industrial structure contains the information of technical level improvement, and there is no need to include PL into the prediction model. Finally, the advanced human capital forecast comparison model is expressed as Equation (6) which is named as Model 2.

$$lnHHC = \frac{1}{\beta}lnALS + \frac{\alpha}{\beta}lnPL + lnUR \quad (6)$$

According to Model 2, the influence mechanism of advanced human capital can be analyzed from economic structure adjustment. Since regions can be regarded as independent economic output sector and can generate input–output correlation through resource flow and policies can affect industrial structure upgrades. Meanwhile, talent flow and knowledge gathering have certain spillover effects (Wu, 2023) [43]. Due to the difference of resources allocation and industry connection, the spillover effect of knowledge has some differences which will affect the high-level human capital formation in different regions. It is necessary to raise advanced human capital in the relatively low levels within the region. Therefore, Hypothesis 2 is proposed as the following:

Hypothesis 2. *Industrial structure upgrade, technology level improvement and urbanization promotion can together boost advanced human capital degrees. Due to the structure and spillover effect the region advanced human capital will have heterogeneity and this heterogeneity can explain the regional coordination gap.*

Table 1. Note meaning of variables.

Category	Abbr.	Implication	Measurement Method
Explained variable	*HHC*	Stock of advanced human capital.	Calculate by measuring the proportion of people with higher education in society, which means this part of people have a college degree or above, using the five-equal length of education year method measurement refer to Morett (2004), Li et al. (2013), Liang et al. (2016) [44–46].
Explanatory variable	*GDP*	Real regional gross regional product: reflected the total output of a region for a certain period.	By deflation of the base period to eliminate the influence of price factors, 2005 is the base period in this paper.
	PL	Independent innovation ability.	Takes the amount of patent authorization as the agency index.
	AIS	The advanced industrial structure.	Calculation formula is: $AIS = \frac{AI}{GDP} + 2\frac{TI}{GDP} + 3\frac{TI}{SI}$.
	UR	Population urbanization, use urbanization rate to represent.	Calculated by the urbanization rate of the permanent resident population, refer to Wu et al. (2018) [47], Wang et al. (2019) [48], Du et al. (2022) [49].
	CS	Physical capital stock.	Using perpetual inventory method, calculation formula is: $CS_{i,t} = (1-\delta_i)\, CS_{i,t-1} + E_{it}; CS_{i,0} = \frac{E_{i1}}{\delta_i+\sigma_i}$. Among them, $CS_{i,t}$ represents the capital stock of phase i is of i province. E_{it} represents phase i province t's constant price fixed asset investment, δ_i represents the depreciation rate of fixed assets in i province, and σ_i represents the growth rate of fixed asset investment in i province. CS_{i0} represents the initial capital stock of i province, and the depreciation rate of fixed assets in this paper is 9.6%, refer to Zhang et al. (2003) [50].

2. Data and Methods

2.1. Data

According to the C–D production function theoretical model, this research selects advanced human capital (*HHC*) as the core explanatory variable, respectively, selects the regional GDP (*GDP*), physical capital stock (*CS*), and independent innovation ability (*PL*) which can refer to technical capital and urbanization rate (*UR*) as explanatory variables in Model 1. The advanced industrial structure (*ALS*), independent innovation ability (*PL*), and urbanization rate (*UR*) are the explanatory variables in Model 2. Thirty provinces panel data of China from 2005 to 2019 are chose in China for regression.

Table 1 is the note meaning of variables which shows the abbreviations, meanings and specific calculation methods of the explained and explanatory variables. Table 2 shows the statistical characteristics of the explained and the explanatory variables. To eliminate the collinearity effect of data instability, a logarithm treatment is performed to absolute number variables, and the results have showed that there is no collinearity among the explanatory variables. Figure 1 shows the kernel density estimation plots of the explained and explanatory variables which can provide skewness and multimodality of valuable indications of explanatory variables. The kernel density estimation plots result indicates that *HHC*, *GDP*, *PL*, *CS*, and *ALS* overall share some degree of similarity in morphological trends and can be viewed as clues for further in-depth analysis.

Table 2. Variable statistical characteristics.

Var	Obs	Mean Value	Standard Deviation	Variance	Minimum Value	Maximal Value	Median	One Quartile	Three Quartiles
LnHHC	450	8.6456	0.8000	0.6340	6.2574	10.1859	8.7507	8.2727	9.1802
LnGDP	450	9.1382	0.9196	0.8457	6.2977	11.0963	9.2306	8.6545	9.7671
LnPL	450	9.1382	1.6327	2.6656	4.3694	13.1757	9.4252	8.2522	10.5976
LnUR	450	3.9583	0.2491	0.6205	3.2910	4.4954	3.9581	3.8024	4.0993
LnCS	450	10.6048	0.8547	0.7306	8.2141	12.4174	10.7281	10.0015	11.2145
ALS	450	4.2155	1.9943	3.9774	2.2048	17.1814	3.6123	3.1232	4.5977

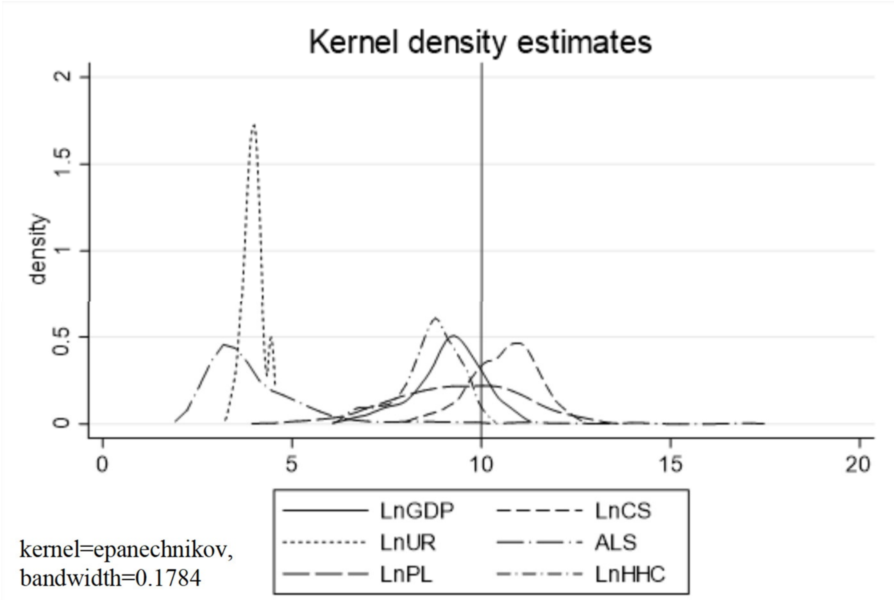

Figure 1. Variables kernel density estimation results.

2.2. Methods

2.2.1. Estimating Screening Prediction Influencing Factors of OLS Model

A double-fixed OLS estimation of individual time points can more accurately reflect the basic characteristics between variables. According to previous theoretical analysis and both Model 1 and Model 2, the OLS estimate of the screening equations are Equations (7) and (8).

$$lnHHC_{it} = \alpha + \beta_0 lnGDP_{it} + \beta_1 LnPL_{it} + \beta_2 LnUR_{it} + \beta_3 LnCS + \varepsilon_{it} \quad (7)$$

$$lnHHC_{it} = \alpha + \beta_0 ALS_{it} + \beta_1 LnPL_{it} + \beta_2 LnUR_{it} + \varepsilon_{it} \quad (8)$$

2.2.2. Introduction of the Selection of the PSO-BP Algorithm

The neural network algorithm is a common prediction method in the field of artificial intelligence at present. BP neural network is widely used in microeconomic behavior prediction, environmental management decision making, agricultural management, and other fields (Sun et al., 2022; Dong et al., 2022; Lu et al., 2021) [51–53]. BP neural network is widely used mainly because it is a multi-layer feed-forward neural network with relatively strong adaptability, generalization, and fault tolerance. Due to the original, the BP neural network may have a possibility of falling into local optimal solution due to the selection of the initial threshold and weight (Sun et al., 2022; Xu Meixian et al., 2022; Li et al., 2022) [51,54,55]. PSO-BP neural network is faster and the results are more accurate (Li et al., 2022) [55]. Thus, to solve this problem, a particle swarm optimization algorithm is used to solve the local optimal solution and overfitting phenomenon based on the use of PSO-BP neural network. In addition, this practice can further improve the model's generalization ability and prediction accuracy. According to the influence factors of human capital screening by the OLS regression for the samples, the target region Beijing–Tianjin–Hebei region and the comparison regions of the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area data are used to fitting the PSO-BP-neural network prediction models of the above provincial level advanced human capital amount between year 2020 and 2025 to obtain the forecasting results.

Figure 2 is the empirical analysis framework of this paper, which can explain the experimental purpose and the main process of selecting prediction variables and also the predicting neural network structure used in this paper.

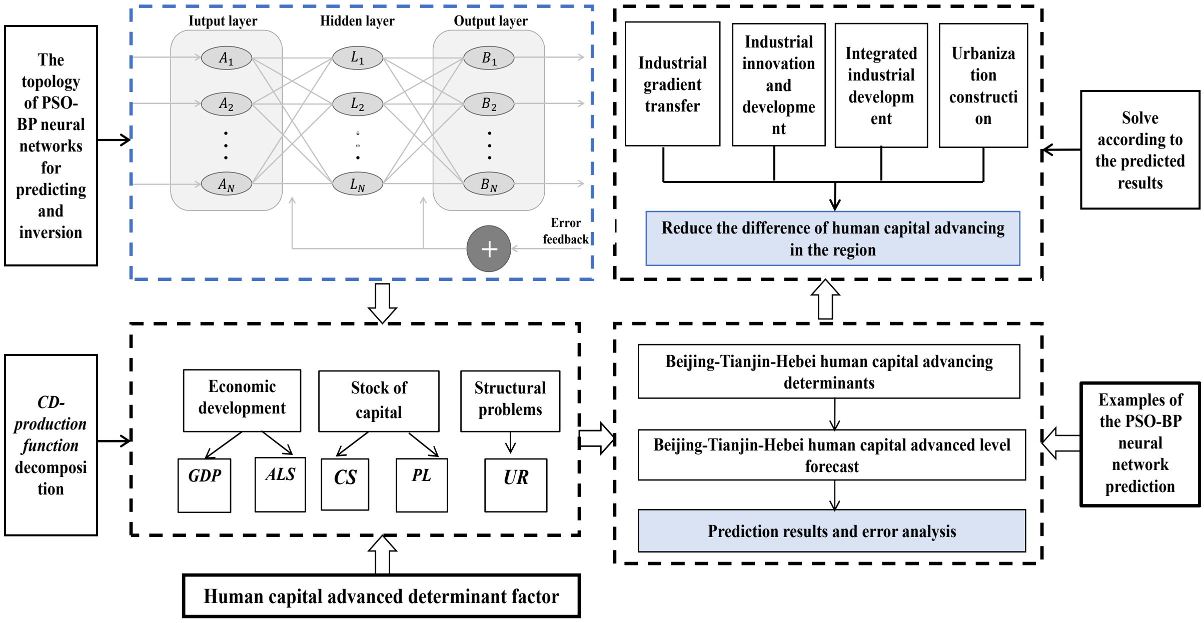

Figure 2. Test framework and description.

3. Forecast Results

3.1. Screening Results of Influencing Factors Based on OLS Model

Table 3 is the estimation results of the two regression models based on Equations (7) and (8). The regression results of Model 1 show that under the framework of Cobb–Douglas production function, the urbanization rate and independent innovation ability both have positive and significant effects on the senior human capital. The GDP and physical capital stock parts are insignificant under the regression Model 1. The regression results of Model 2 shows that when considering the industrial structure, and technical capital substitute for physical material capital and urbanization rate technical capital. Technical capital refers to the variable of independent innovation ability. It can be found that industrial structure, technical capital and urbanization all have significant positive impacts on senior human capital which means these variables all have positive role on senior human capital. In addition, it can be seen that the replacement of GDP by an advanced industrial structure can better reflect the demand for regional economic development potential for advanced human capital.

Table 3. Estimation results of individual and time points both-fixed models.

LnHHC	Model 1	Model 2
ALS		0.0282 ** (−0.0107)
LnGDP	0.0134 (−0.1138)	
LnPL	0.0432 * (−0.0238)	0.0423 * (−0.0239)
LnUR	0.4822 *** (−0.1217)	0.6485 *** (−0.1377)
LnCS	−0.0115 (−0.044)	
_CON	6.3077 *** (−0.644)	5.2724 *** (−0.6252)
IF	Yes	Yes
TF	Yes	Yes
R^2	0.9774	0.9776
p ($p > F$)	0	0

Note: "( )" is a regression standard error, ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

The estimated coefficients of model variables were unchanged in the robustness test of Models 1 and 2, indicating the robustness of the models. The regression results of the two models show that the high-quality development of the regional economy, including the growth of quantity, the rationalization of structure, innovative development, and the improvement of urbanization level all have a great impact on the level of advanced human capital stock. This basic conclusion also supports the previous research hypothesis. Moreover, Model 2 fits better than Model 1, indicating that the fitting relationship among variables is better.

3.2. Based on the PSO-BP Prediction Results

In this study, the significant explanatory variables of Model 1 and Model 2 are used as the prediction input variables of advanced human capital, respectively, to predict the stock of advanced human capital in the Beijing–Tianjin–Hebei region in 2020–2025, which means the 14th Five-Year Plan period and which is have quite important meaning for China economic development. According to the significant predictor of OLS, Model 1 uses the number of patents and urbanization, and Model 2 uses patents, urbanization, and industrial structure. Table 4 illustrates the prediction's mean absolute percentage, error (MAPE), and root mean squared error (RMSE). MAPE and RMSE can be used to determine whether there is an ideal fitting effect. From Table 4, it can be seen that the overall prediction results are ideal. In addition, compare Model 1 and Model 2, it can be seen that the MAPE and RMSPE are better in Model 2 than in Model 1 on the whole. Figures 3 and 4 present the error distribution of the Beijing–Tianjin–Hebei region predicted by Models 1 and 2. It can be seen that, except for the 3 years of the starting fitting prediction, the fitting prediction error in other years is relatively small, and the fitting prediction error is relatively small after 2018, thus ensuring the accuracy of the model prediction.

Table 4. Prediction error of the PSO-BP model in Beijing–Tianjin–Hebei region.

Province	Model 1		Model 2	
	MAPE	RMSE (10^3)	MAPE	RMSE (10^3)
Beijing	5.09%	0.11	1.19%	0.11
Tianjin	2.40%	0.14	0.56%	0.06
Hebei	5.99%	0.55	4.42%	0.81

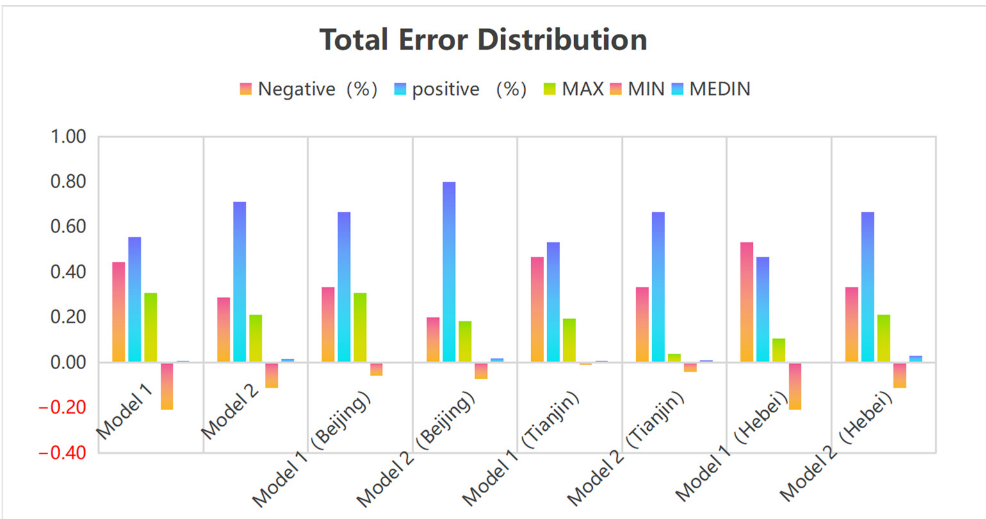

Figure 3. PSO-BP Total error distribution in Beijing–Tianjin–Hebei region (Model 1, Model 2).

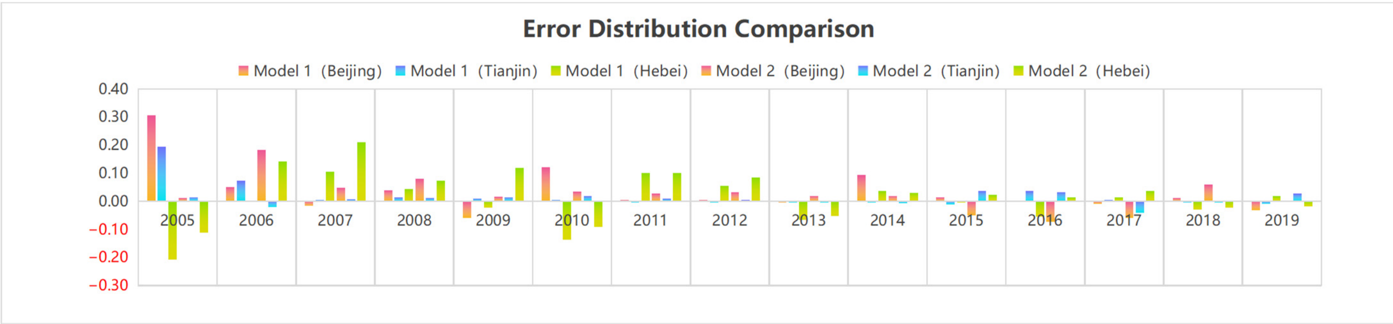

Figure 4. PSO-BP error distribution Comparison in Beijing–Tianjin–Hebei region (Model 1, Model 2).

Specific prediction results can be found in Table 5. In general, the forecast trend of Beijing in Model 1 have more obviously continuing rising, and the forecast trend of the human capital of Beijing in Model 2 is stable developing. The human capital forecast trend of Tianjin in Model 1 is stable development and the trend of Hebei is steady developing in both Models 1 and 2. Due to the different trends of forecast results generated from different input variables, it can be seen that economic aggregate has a greater impact on the forecast of Tianjin and Hebei, while economic quality has a greater impact on the forecast of Beijing. In addition, Figures 5 and 6 can more intuitively reflect the changing trend of Models 1 and 2, especially the gap and Figures 7 and 8 report the changing trend of advanced human capital per capita in the Beijing–Tianjin–Hebei region under Models 1 and 2. To sum up, it can be seen that in Models 1 and 2, there is a similarly consistent trend. The trend in this area have showed that from the perspective of the total trend of senior human capital, Hebei is at the medium level, but from the perspective of the changing trend of the per capita level of senior human capital, there is a large multistep gap among Hebei, Beijing, and Tianjin. This means if the natural growth rate of the 13th year period is maintained, the gap between Hebei, Beijing, and Tianjin can be difficult to narrow down.

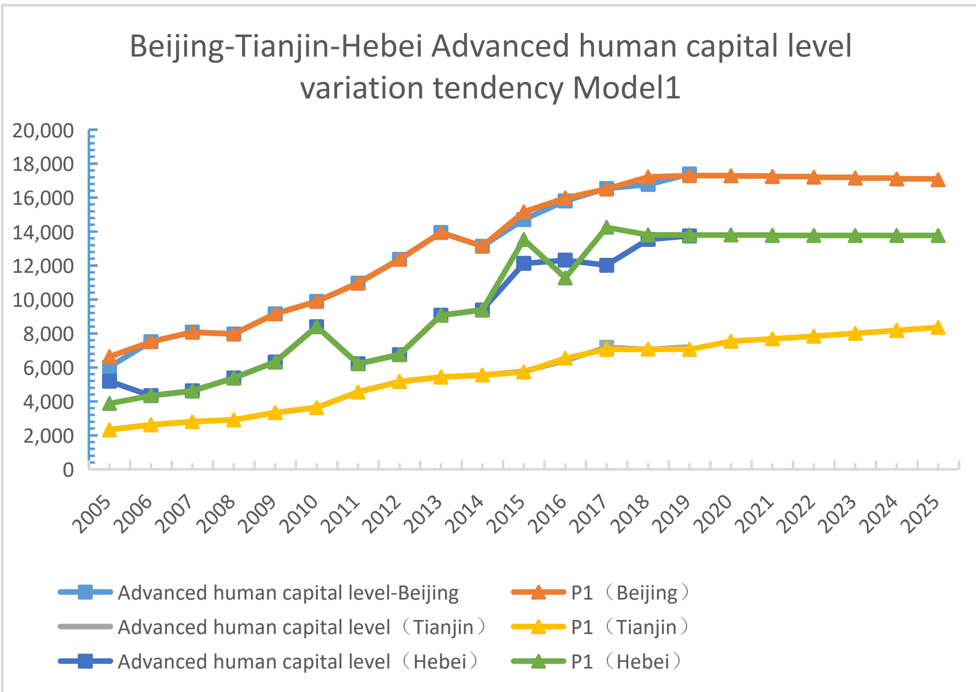

Figure 5. Change trend of advanced human capital in Beijing–Tianjin–Hebei region (Model 1).

Table 5. Advanced human capital stock forecast table in the Beijing–Tianjin–Hebei region (2020–2025).

		Advanced Level of Human Capital			Advanced Human Capital Level (Per Capita)		
	Year	**Beijing**	**Tianjin**	**Hebei**	**Beijing**	**Tianjin**	**Hebei 1**
Model 1	2020	17,516.69	7530.93	13,584.61	7.87	4.74	1.69
	2021	18,451.41	7733.38	13,669.25	8.02	4.79	1.61
	2022	19,251.92	7826.98	13,808.05	8.09	4.76	1.54
	2023	19,666.50	7867.69	13,898.24	7.99	4.71	1.47
	2024	19,815.89	7884.59	13,943.63	7.79	4.64	1.40
	2025	19,858.93	7890.04	13,962.88	7.55	4.56	1.33
Model 2	2020	17,276.57	7541.79	13,795.87	7.76	4.75	1.72
	2021	17,239.43	7682.66	13,772.42	7.49	4.75	1.63
	2022	17,196.79	7836.22	13,768.24	7.23	4.77	1.54
	2023	17,150.76	8002.29	13,767.39	6.97	4.79	1.46
	2024	17,101.88	8177.06	13,767.19	6.72	4.81	1.38
	2025	17,051.35	8355.89	13,767.14	6.49	4.83	1.31

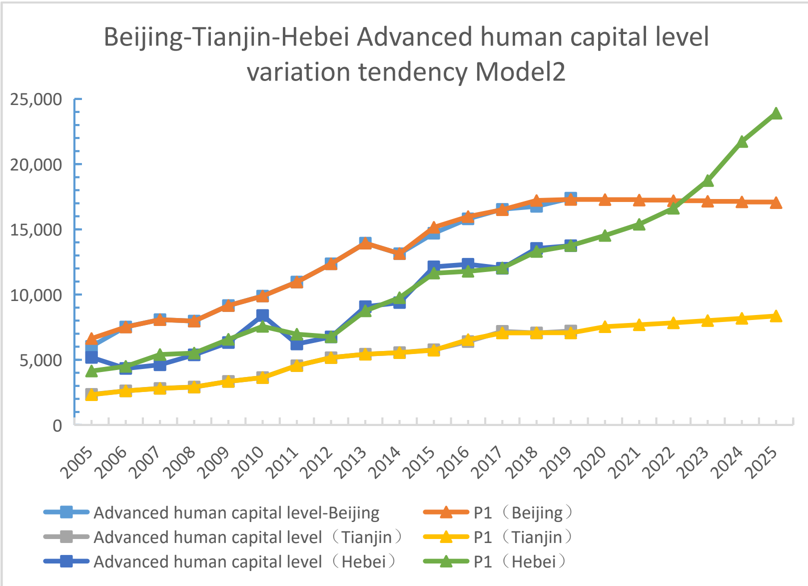

Figure 6. Change trend of advanced human capital in Beijing–Tianjin–Hebei region (Model 2).

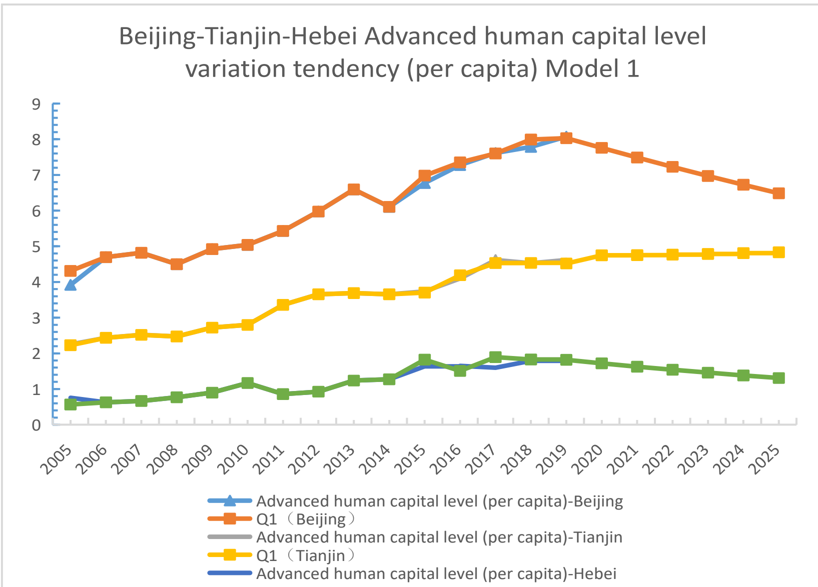

Figure 7. Change trend of advanced human capital per capita in Beijing–Tianjin–Hebei region (Model 1).

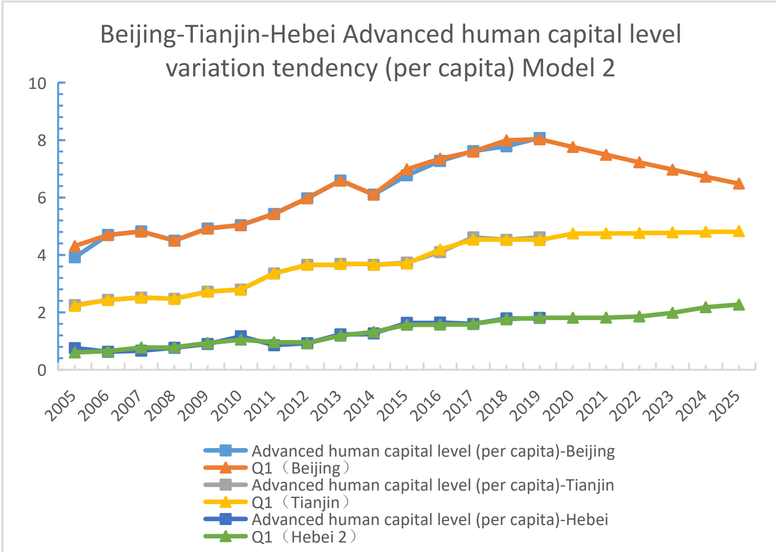

Figure 8. Change trend of advanced human capital per capita in Beijing–Tianjin–Hebei region (Model 2).

3.3. Comparison with the Forecast Results of Advanced Human Capital Gap in the Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area

To further confirm the research hypotheses 1 and 2, and also to reveal the characteristics of the advanced human capital gap in the Beijing–Tianjin–Hebei region to obtain more accurate conclusions, a forecast comparison is put out to find the characteristics of advanced human capital in the Yangtze River Delta region and the Guangdong–Hong Kong–Macao Greater Bay Area of the same period (2020–2025). For this purpose, the same input variables and input methods are used to construct a PSO-BP neural network fitting prediction model. Table 6 is the prediction error of the PSO-BP model in contrast regions, it shows that the error rate is quite small and the fitting effect meets the requirements. Tables 7 and 8 are the overall advanced human capital and per capita human capital of the comparison region. It can be seen that in the compared regions by contrast the gap of regional advanced human capital is relatively small, and there are no gradient differences within the same regions. However, Figures 9 and 10 show that Guangdong province, which belongs to the Guangdong–Hong Kong–Macao Greater Bay Area has relatively higher advanced human capital than the provinces in the Yangtze River Delta region. However, from Figures 11 and 12 which reflect the forecast trend of regional per capita advanced human capital development, it can be seen that the Shanghai municipality which in the Yangtze River Delta region is at a relatively high level. This trend is in sharp contrast with the rest contrast areas. In addition, in the comparison regions there is an obvious convergence trend of the per capita advanced human capital in the forecast period.

Table 6. Prediction error of the PSO-BP model in comparation regions.

Province	Model (1)		Model (2)	
	MAPE (%)	RMSE (10^3)	MAPE (%)	RMSE (10^3)
Shanghai	2.70%	0.30	3.63%	0.43
Jiangsu	3.94%	0.75	3.69%	0.69
Zhejiang	2.66%	0.32	3.24%	0.52
Anhui	9.52%	0.81	8.81%	0.79
Guangdong	4.55%	1.12	3.76%	0.92

Table 7. Prediction results of advanced human capital stock in comparation regions (Total/2020–2025).

Total	Year	Shanghai	Jiangsu	Zhejiang	Anhui	Guangdong
Model (1)	2020	12,032	21,688	14,910	12,719	27,022
	2021	11,888	22,110	14,907	14,004	26,372
	2022	11,765	22,511	14,906	14,591	28,722
	2023	11,604	22,839	14,908	15,359	27,882
	2024	11,413	23,069	14,865	15,614	26,384
	2025	11,208	23,208	14,877	15,888	23,687
Model (2)	2020	12,597	22,033	14,394	10,948	25,604
	2021	14,189	21,933	14,425	11,538	25,359
	2022	14,572	21,929	14,535	11,263	25,159
	2023	14,841	21,561	14,853	11,670	25,116
	2024	14,987	21,325	14,168	11,238	25,111
	2025	15,054	20,992	14,676	11,491	25,111

Table 8. Prediction results of advanced human capital stock in comparation regions (Per/2020–2025).

Per	Year	Shanghai	Jiangsu	Zhejiang	Anhui	Guangdong
Model (1)	2020	4.95	4.88	4.83	4.75	4.67
	2021	2.68	2.72	2.77	2.80	2.82
	2022	2.51	2.48	2.45	2.41	2.37
	2023	1.98	2.16	2.23	2.33	2.35
	2024	2.31	2.22	2.38	2.28	2.12
	2025	4.95	4.88	4.83	4.75	4.67
Model (2)	2020	5.18	5.83	5.98	6.08	6.13
	2021	2.72	2.70	2.69	2.64	2.60
	2022	2.43	2.40	2.38	2.40	2.26
	2023	1.70	1.78	1.72	1.77	1.69
	2024	2.19	2.14	2.09	2.05	2.02
	2025	5.18	5.83	5.98	6.08	6.13

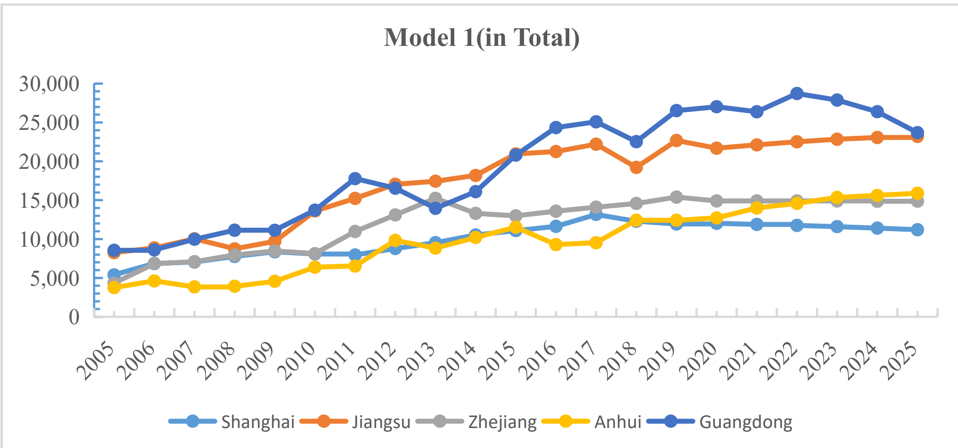

Figure 9. Change trend of advanced human capital in PSO-BP (Model 1) in comparation regions.

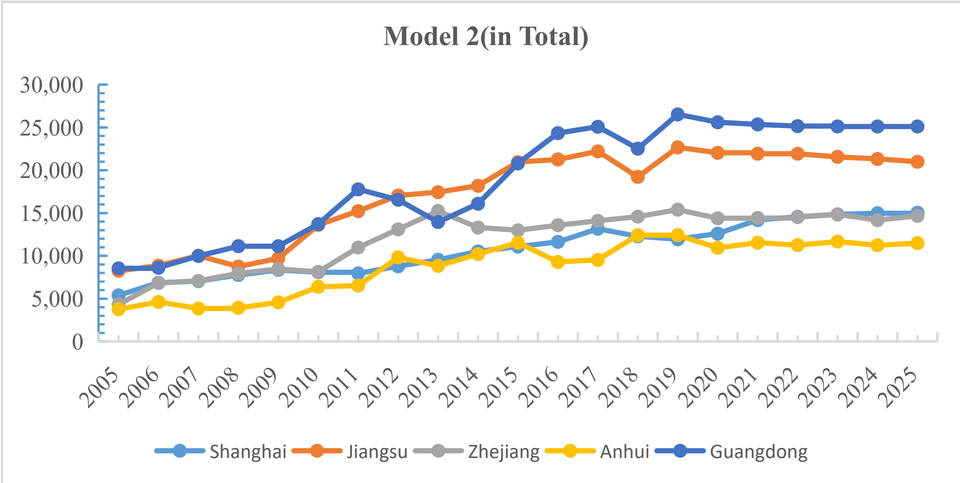

Figure 10. Change trend of advanced human capital in PSO-BP (Model 2) in comparation regions.

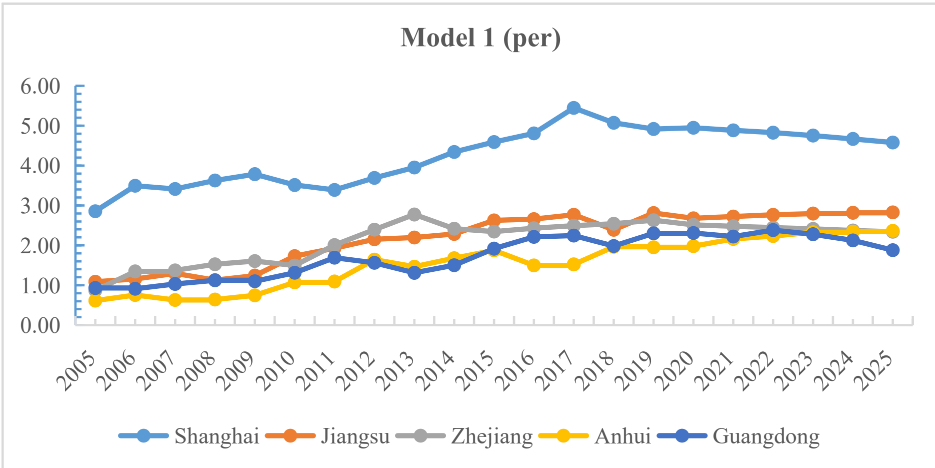

Figure 11. Change trend of advanced human capital in PSO-BP (Model 1) in comparation regions.

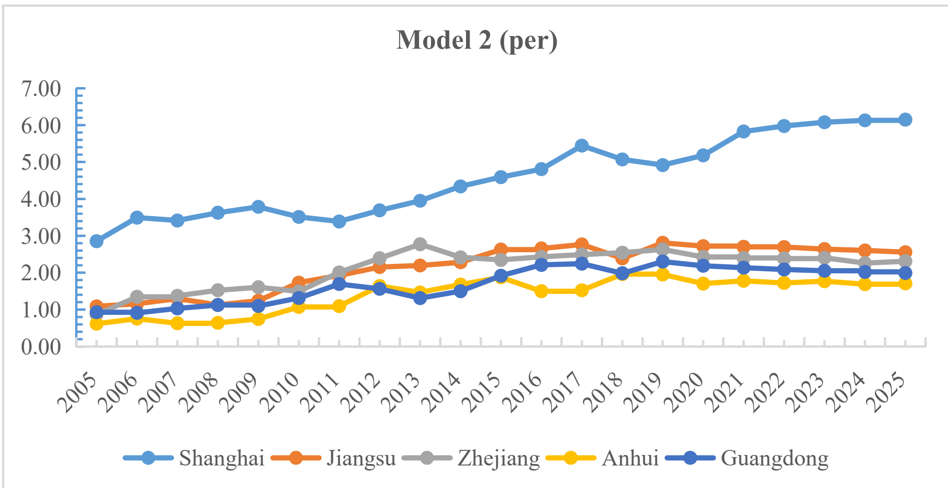

Figure 12. Change trend of advanced human capital in PSO-BP (Model 1) in comparation regions.

Meanwhile, compare these results with advanced human capital forecast results of the Beijing–Tianjin–Hebei region in Section 3.2 in Table 5 and Figures 5–8 the following two results can be obtained. On the one hand, judging from the perspective of total advanced human capital, the rank of total amount of advanced human capital in the above three regions is as follows. In 2020, the rank order was Guangdong, Jiangsu, Beijing, Zhejiang, Hebei, Anhui, and Tianjin, and in 2025, the rank order is Guangdong, Jiangsu, Beijing, Anhui, Zhejiang, Hebei, Shanghai, and Tianjin based on Model 1. In addition, between Model 1 and Model 2, there are some quantitative differences between the province of Shanghai, Anhui, Hebei, and Beijing. The results of Model 2 show that from the perspective of structural optimization, Shanghai and Beijing have more reasonable and advanced trends, the forecast trend of advanced human capital in Model 2 is much better. On the other hand, from the perspective of per advanced human capital, the rank order in 2020 was Beijing, Shanghai, Jiangsu, Zhejiang, Anhui, Tianjin, Hebei and in 2025 it will be Beijing, Shanghai, Jiangsu, Zhejiang, Anhui, Tianjin, Guangdong, and Hebei in Model 1. In Model 2 in 2025, there is also have some difference. Anhui and Jiangsu are higher than Shanghai and other compared provinces, and the overall per advanced human capital forecast result is slightly higher than the Model 1 forecast result. In the Model 2's forecast results in the Beijing–Tianjin–Hebei region, Beijing's per advanced human capital is slightly lower than model 2 and the per advanced human capital results in Tianjin and Hebei is slightly higher than the results in model 1. This trend should be paid more attention. Especially when in the defibering of non-capital functions, how to maintain the advanced characteristic of Beijing industry is a question need to note.

4. Conclusions and Discussion

The purpose of this paper is to offer an accurate forecast method for advanced human capital stock. In this study, by filtering out the influencing factors and established PSO-BP neural network prediction model, an accurate forecast of the advanced human capital stock of 2020–2025 in the Beijing–Tianjin–Hebei region have been conducted and for comparison the same kind of prediction in Yangtze River Delta and the Guangdong–Hong Kong–Macao Greater Bay Area of the same period is also conducted. There are two main findings, from both the method application and practical value aspects. On the one hand, from the forecast method application, the research found when using PSO-BP neural network prediction for forecast regional advanced human capital stock, it has excellent fitting accuracy and the prediction results are accurate. It has shown that this method is a great improvement of the original GM (1,1) and ARIMA model which is also used for human capital stock prediction. On the other hand, specifically, there is a gradient gap in advanced human capital stock in the Beijing–Tianjin–Hebei region. However, in contrast, the advanced human capital in the Yangtze River Delta region and the Guangdong–Hong Kong–Macao Greater Bay Area does not follow the same trend. When considering the predictive influences filtered by OLS regression, it is obvious that the Beijing–Tianjin–Hebei region has always had a relatively large regional development gap. It has long formed the poverty belt around Beijing under the influence of many factors (Lin, 2010; He et al., 2018) [56,57], and this situation hindered the overall development level of Beijing–Tianjin–Hebei region. From the second and third part of the prediction study, it can be found that the gap lies in economic aggregate, industrial structure, innovation ability, and many other aspects which together have caused the above results. If the above problems cannot be solved well, it is difficult to form a sustainable regional coordinated development model and narrow the advanced human capital gap in this region. While, if the advanced human capital gap cannot be reduced, it will further restrict the sustainable development capacity of this region. With the popularization of higher education, the structure of the labor force is in a deep change.

Compared with previous findings in the literature, the shackles of the coordinated development of the Beijing–Tianjin–Hebei region is not just the differences in the governance systems (Bian et al., 2020) [21], human capital does play a vital role in the development of this region (Xiao et al., 2022) [25]. The PSO-BP neural network prediction results have showed that, there does exist such a trend that, when the advanced human capital level is in different degrees, the impact of advanced human capital on industrial structure and green development is quite different. This results have consistency with the conclusion drawn by Liang et al., (2023) [23] from empirical analysis using a threshold regression.

Meanwhile, it can be found that there is a significant difference between the expectation of advanced human capital between economic structural adjustment and economic aggregate changes. Areas with better industrial foundation and a booming innovation atmosphere are more sensitive to the reflection of economic structural adjustment, such as Beijing, Shanghai, Jiangsu, and Zhejiang provinces. In addition, the stock base of advanced human capital is also has a significant impact, such as Anhui, Guangdong and Tianjin. Another point different from the previous studies is that, the study provides a predictive analysis of the specific advanced human capital gap, though the comparison with the distribution characteristics of advanced human capital in the Yangtze River Delta region and the Guangdong–Hong Kong–Macao Greater Bay Area of the same forecast period, it can confirm that the characteristics of advanced human capital distribution in this region have obvious particularity. This particularity can facilitate the formulation of targeted and coordinated development policies.

Due to the result being most based on China's regional development characteristics, the study is more in line with China's reality. Whether it can be extended to other developing economies, it is in need to consider whether the economy has similar cultural traditions, development model, and policy guide. This could be the limitations of this work. At the same time, the supervised learning method used to predict the advanced level of human capital is a good attempt of applying artificial intelligence in multi-disciplines, and there will be more application of the related fields in the future.

The present study provides some practical implications for Beijing–Tianjin–Hebei region further development. Firstly, for regional agglomeration, there is a need for further innovative industry gradient transfer and urbanization measures, to further deepen Beijing's political, cultural, and foreign exchanges, and science and technology innovation center, effective dredge the non-capital function, promote the industry optimization layout, driving the rapid economic development in Tianjin, Hebei. Secondly, upgrading human capital by following the new trend of development concept, actively developing higher education for social needs, pay attention to the obvious areas gradient gap and retain the talents needed for regional development. So as to break though the phenomenon of talent isolated island of Beijing, and form a regional connected talent market to optimize the regional labor structure.

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