An Exploratory Factor Analysis for Measuring Human Capital Development After Global Economic Recession

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Abstract. In recent years, the fluctuation of economic growth and ever more uncertain events or emergencies have posed a serious threat to the sustainable development of human capital. This paper constructed a multi-dimensional index of human capital development (HCD) from the aspect of education, health, labour, population and modernization. Subsequently, an exploratory factor analysis (EFA) was adopted for measuring the level of HCD after global economic recession in 2008. As revealed from the results, the global recession posed a negative effect on the China's HCD, while it soon changed to positive growth. The human capital indicators that related to education and science played main role in the growth of HCD.

Keywords: human capital development · exploratory factor analysis · economic recession

1 Introduction

As the whole domain of our world struggles to encounter the COVID-19 pandemic, its poses the biggest threat to the international economy after global economic recession in 2008–2009 [1]. This threat mainly appeared in the instability of labour demand from enterprises, which may cause public panic for graduate students as difficult to obtain initial employment. More broadly, individuals, industries, public sectors and even each part of social system are exposed to the high risk of social uncertain. To deal with these uncertain risks, developing more sustainable human capital is a rational choice that can be broadly defined as the stock of knowledge, skills and other personal characteristics embodied in people that help them to be more productive. Investment in human capital includes investment in formal education, but also informal and on-the-job learning and work experience. However, related studies mainly adopted single indicator to represent the human capital development (HCD), such as employee educational years, average

R. B. B. M. Hussain et al. (Eds.): ICHSSR 2023, ASSEHR 765, pp. 1046–1052, 2023.
https://doi.org/10.2991/978-2-38476-092-3_129

enrollment rate and health conditions [2, 3]. It will lead to the deviation of HCD measurement, thus affecting the accuracy of research results [4]. Although many researchers realized the complexity of HCD concept, the selection of proxy variable is still random. Organisation for Economic Cooperation and Development (OECD) have put forward the definition of human capital, that is, personal knowledge, technology, ability and attributes that promote the creation of personal, social and economic well-being [5]. This definition indicates that human capital is a multi-dimensional concept and cannot be simply measured. Base on this definition, many studies have further developed more comprehensive indexes for measuring the level of HCD. For instance, Pen World Tables (PWT) database gave a HCD index based on schooling and returns to education [6], OECDs' new measures of human capital relies on a production function approach that incorporate multi-factor productivity, capital deepening; and employment rate [7]. These HCD index are more suitable to the high developed regions, while ignoring the situation of developing countries. Based on the above, this paper will construct a comprehensive framework to reveal the dynamics of human capital from 2008 to 2020 in China. To measure the level of HCD, an exploratory factor analysis (EFA) is adopted to identify the main factors within HCD index. Finally, some implications for improving the level of HCD are put forward.

2 Methodologies

2.1 Construction of HCD Index

Human capital refers to the condensed in laborers, through the investment of capital. The cost is transformed into the capital cost of laborer's skills and techniques, which is the sum of the value of laborer's knowledge level, technical level, work ability and health status. Considering the data availability and international comparability, this paper measures the HCD based on five dimensions: education, demographic, labor market, health level and modernization level. And a total of 22 indicators related to HCD are obtained for exploratory factor analysis (Table 1).

2.2 Exploratory Factor Analysis

Most related studies for measuring HCD are mainly adopted one-dimensional indicators. However, we cannot ensure these indicators represent all aspects of HCD. Besides, most indicators of human capital contain measurement errors, which will lead to low-quality data and biased estimates. To measure HCD more accurately, we use EFA to determine the commonness of different indicators and divide these indicators into specific factors. The EFA model can be written as:

$$x_i = \Delta\xi_i + \varepsilon_i \tag{1}$$

where x_i is an n-dimensional vector, which contains n indicators of the measurement subject i ($i = 1, 2\ldots, K$) (i.e., human capital-related indicators in this paper); Δ is an $M \times K$-order factor load matrix; ξ_i is a latent variable with a zero mean and positive

Table 1. The index for HCD measurements

Education	**Health level**
1. Number of primary school students	13. Infant mortality
2. Number of junior high school students	14. Maternal mortality
3. Number of senior high school students	15. Life expectancy
4. Number of college students	16. Survival rate
5. Adult literacy rate	**Labour market**
6. Average years of education	17. Wage levels
7. Number of employees with primary education	18. Unemployment rate
8. Number of employees with secondary education	**Modernization level**
9. Number of employees with higher education	19. Technology market turnover
10. Number of employees above higher education	20. R&D personnel at that time
2. Demographic features	21. Number of patents authorized per thousand people
11. Population	22. Export volume of high-tech products (M4)
12. The rate of population aging	

definite variance; and ε_i is the random error term, which is assumed to be independent of the latent variable. Under the above assumptions, the covariance matrix of x_i is:

$$\Xi = \Delta\Phi\Delta\prime + \Omega \quad (2)$$

where Ξ is a parameterized covariance matrix, which can be decomposed into the covariance matrix of factors Φ, the sum of the diagonal covariance matrix Ω of the sum error term. The maximum likelihood estimation (ML) method is used for the estimation of the model, and the logarithmic form can be written as:

$$\mathrm{lnL} = \ln|\Xi| + \mathrm{tr}\left[S\Xi^{-1}\right] \quad (3)$$

where S represents the sample covariance matrix, and minimizing the fitting function means determining the values of all unknown parameters to make the covariance matrix of potential variables as close as possible to the sample covariance matrix.

Subsequently, the number of factors representing HCD is determined based on the gravel map, which plots the number of factors related to the eigenvalue of the indicator covariance matrix. There are generally two ways to interpret this diagram. According to Kaiser's law, only factors with eigenvalues greater than 1 should be retained. Another method is to find an "elbow" in the gravel map, that is, the remaining factors decline in an approximately linear manner, and only the factors above the elbow are retained.

After determining the number of factors, it is likely that the factors provided by the model results are difficult to explain. In this case, the rotation factor loading can produce a more interpretable solution because the matrix has a simpler structure. Ideally, each indicator is related to as few factors as possible. The rotation technique we use to explain factors is the oblique rotation axis method, so that there can be a correlation between factors and the correlation of the columns of the factor load matrix can be minimized. Therefore, a good indicator will have a high factor load on one factor and a low load on the other factors. All indicators have a factor score of various dimensions (factors). Based on these factor scores, Bartlett's prediction can be established, that is, the best linear unbiased prediction of factor scores:

$$\hat{\xi}_i = \Phi \Delta / \theta^{-1} x_i \tag{4}$$

These factor scores are used to reflect the level of HCD. Among them, θ is the correlation matrix of the original variable.

2.3 Data Source

The data used in this paper were obtained from the China National Statistical Yearbook, China Labor Statistical Yearbook and the China Education Statistical Yearbook. Due to the lack of population data aged 6 and above in 2010, we assumed that children aged 0–5 account for 35% of the population aged 0–14. In addition, when calculating the average number of years of education, we used the formula: average years of education = (sample population with primary school education * 6 + junior high school * 9 + senior high school * 12 + junior college and above * 16)/total population aged six and above.

3 Results

The correlation coefficients between most indicators are high and their linear relationship are strong, which is suitable for extracting common factors. According to the gravel map (Fig. 1) and Kaiser's rule, there are three common factors and their cumulative variance contribution rate reaches 93.284%. It means the integrity of the information is well preserved (Fig. 1).

The explanation rate of the total variance of 3 common factors is shown in Table 2.

The factor load matrix of human capital variables and their degree of variance explanation are obtained by the maximum variance method. According to the rotating component matrix, the indicators from education and modernization represent the level of national education and science standards. Therefore, we name them as Factor 1 that include educational and scientific human capital (ESHC); the indicators from demographic features and labour market reflect the scale of current working-age population, so we defined Factor 2 as working-age human capital (WAHC); the indicators about mortality and survival rate reflect the human resources supply in the future, so we defined Factor 3 as potential human capital (PHC).

Based on Fig. 2, we can draw the following findings: (1) the human capital related to education and science fallen into the low valley in 2009 and turned to positive growth

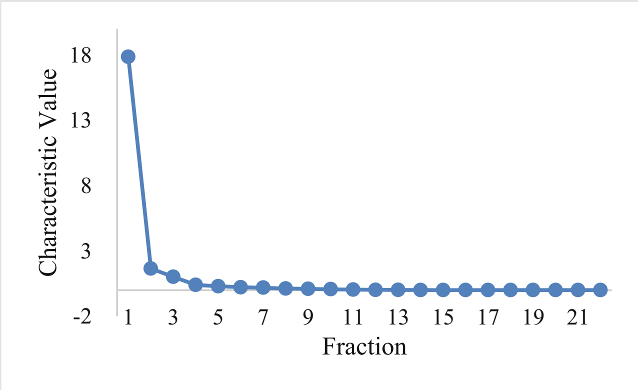

Fig. 1. Human capital factor analysis gravel chart

Table 2. The explanation rate of the total variance

Common factors	Initial eigenvalue			Extraction load square sum			Rotation load square sum		
	Total	Variance percentage	Cumulative percentage	Total	Variance percentage	Cumulative percentage	Total	Variance percentage	Cumulative percentage
1	17.86	81.17	81.17	17.86	81.17	81.17	12.88	58.56	58.56
2	1.65	7.49	88.66	1.65	7.49	88.66	5.80	26.35	84.91
3	1.02	4.63	93.28	1.02	4.63	93.28	1.84	8.38	93.28

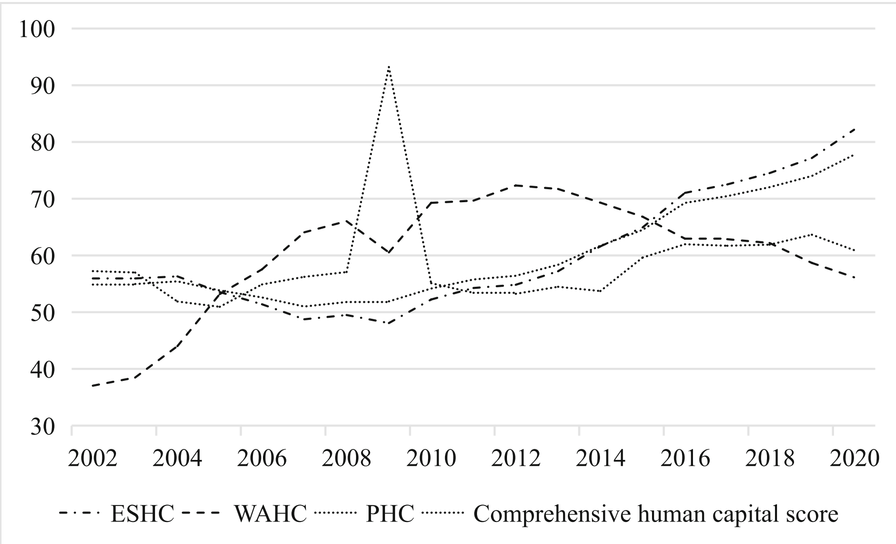

Fig. 2. Score chart of the level of HCD

subsequently. Especially after the year of 2016, the level of ESHC increased remarkably, which mainly due to China's increasing investment in the area of education and science; (2) the human capital related to working population has shown a steady growth in the early stage, while countered a huge impulsion in 2008 crisis. As the higher unemployment and infant mortality rates fallen gradually, the level of WAHC began to declined after 2012; (3) PHC has been stable since 2002, except for a sudden increase in 2009. After the economic recession, the development of PHC has been at a low level; (4) the comprehensive human capital was in a state of steady growth from 2002 to 2020. Although PHC showed an outlier around 2009, ESHC weighed heavily in the overall score and offsetting much of the volatility. Therefore, compared with PHC and WAHC, it is more important to strength the ESHC in the aspects of educational standard, scientific research and health level for the improvement of comprehensive human capital.

4 Conclusions

This paper uses exploratory factor analysis (EFA) to calculate the development of comprehensive human capital in China. The main conclusions are as follows: (1) the HCD are constituted by three common factors that accounted for the accumulative variance contribution of 93.284%; (2) the global recession in 2008 posed a negative effect on the China's HCD, while it turned to positive growth afterward; (3) the human capital related to education and science was the core element in HCD; (4) as the birth population decreases, the potential supply of human capital in China is expected to slow.

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