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Influences of Talent Cultivation and Utilization on the National Human Resource Development System Performance: An International Study Using a Two-Stage Data Envelopment Analysis Model

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Abstract: To enhance national competitiveness, countries are committed to building a National Human Resource Development (NHRD) system to develop talents. However, studies have rarely investigated the internal development process of the NHRD system and the performance at the system and sub-system levels. Thus, this study constructed the performance evaluation model of the NHRD system from a two-stage process efficiency perspective that first cultivates talents and then uses the talents produced to create value. In addition, considering the problem of international talent flow and the time-lag effect, the bad output and the time-lag between inputs and outputs were incorporated into the model. The subjects included 60 countries, including Argentina, China, and OECD member countries. The results reveal that countries that excel at nurturing talents do not necessarily have the ability to effectively use talents to create value. Only having high-efficiency talent cultivation cannot strengthen competitiveness. Sensitivity analysis was also conducted to identify the input that affects talent cultivation and utilization efficiency, which could be used as a reference for competitiveness and NHRD performance improvement.

Keywords: performance evaluation; relative efficiency; talent cultivation; talent policy; data envelopment analysis; two-stage model; SBM model

MSC: 90C08

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1. Introduction

As the world of work changes rapidly around us, it is more and more necessary to have more information available to benchmark how countries are competing against their peers and to understand the trends affecting talent flows and talent competitiveness to improve national performance [1]. For example, which countries are setting the pace in talent competitiveness? Who is falling behind? How can countries improve the way countries enable, attract, grow, and retain talent? Among the studies of talent competitiveness, the Global Talent Competitiveness Index Report (GTCI), released by INSEAD every year, is the most effective evaluation index system. It mainly constructs the evaluation index model from two aspects of talent input and talent output to analyze the talent competitiveness of countries worldwide. The GTCI combines an assessment of what governments do to produce and acquire talents (input) and the kind of skills that are available to them as a result (output) [1].

Over the last decade, both industry and academics have agreed that if a country has more talents and can effectively guide talents to exert their value creation ability, they will gain sustainable competitive advantages, increase productivity, drive economic growth, and thus improve national competitiveness [2–4]. After that, many countries are committed to developing a National Human Resource Development (NHRD) system to nurture, attract, and retain various talents [5–7]. Thus, it is necessary to establish a performance evaluation model of NHRD that can be used to examine the effectiveness of national talent cultivation and talent utilization. However, the composition of the NHRD system is multi-dimensional and complex, not only including multiple subsystems, but also interacting with each other, yet few studies have investigated the internal impact process of the NHRD system and the performance of the subsystem level [8]. In addition, when evaluating the performance of the NHRD system, the problem of international talent flow and the time lag effect of system operation are mostly ignored, which will lead to the overestimation of performance and the problem of inconsistency with the real situation [8–10].

Traditional performance analysis and evaluation neglect the context between various activities in a system when measuring the input–output efficiency and, consequently, cannot effectively present the managerial implications and developmental direction of the policies [11]. Thus, intermediate processes are regarded as a black box and have not been explored. Moreover, talent development activities are a continuous process, so the effect of time-lag must be considered when constructing evaluation models. Some studies have pointed out that considering the time-lag effect between input and output is one of the important factors to improve the validity of assessment [11]. To more accurately reflect the systematic process of how a country enhances its national competitiveness through talent cultivation and utilization, an NHRD system performance evaluation model with the time gap of at least one year between the inputs and outputs was conducted from the perspective of process efficiency. In the first stage, the efficiency of national talent cultivation was explored, that is, the efficiency of countries to output talents that meet the needs of the market environment through the investment of various resources. In the second stage, the efficiency of talent utilization was explored, that is, to reinvest the output of the first stage and evaluate the efficiency of a country's process of using these talents to generate competitiveness (e.g., economic- and knowledge-based value creation). The two-stage efficiency evaluation model of the NHRD system in this study could objectively compare the efficiency of human resource investment in different countries and fully reflect the value creation process of talent utilization to ultimately enhance national competitiveness. In addition, the problem of the loss of value or competitiveness caused by a country's inability to make good use of talents was also considered. Therefore, the unintended output indicator of "brain drain" was included as a potential loss for the efficiency of talent utilization in this study.

In summary, the two-stage data envelopment analysis (DEA) method was used in this study to compare the performance of the decision-making units (DMUs) of 60 countries, including OECD member countries, as DEA has been widely used for ranking the performance of DMUs. Besides understanding the cultivation and utilization of talents in various countries, it can also provide benchmarks to be used as a reference for other countries to formulate talent cultivation and utilization strategies in the future. Finally, this study also conducted a sensitivity analysis to identify important input indexes that affect the cultivation and utilization of talents, which could be used as improvement suggestions for inefficient DMUs.

This paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the research design adopted in this paper, including the research framework, selection of input and output variables, and methodology. Section 4 illustrates the empirical results, including efficiency analysis and sensitivity analysis. Finally, Section 5 offers the research conclusions and implications, as well as the limitations of the research and suggestions for future research.

2. Literature Review

2.1. Definition of Talent

At present, scholars do not have a unified definition of talent. Goleman [12] pointed out that in professional work, the value created by excellent employees is ten times that of ordinary employees. The Chartered Institute of Personnel and Development states that "talents are those who can have the greatest impact on organizational performance through direct contribution or by showing high-quality potential in the long term" [13]. In the study of Scott, McMullen, and Royal [14], 70% of the testees defined talents as employees with good performance, high potential, or key positions in an organization. Although scholars hold different views, the above literature shows that people who are considered talented all have unique abilities, can deliver better performance than ordinary people in specialized fields, and create great value for an organization. The talents that this study discusses are those who can help the national industry and economic development and enhance or create national competitiveness. Therefore, this study referred to past scholars' definitions of talents and redefined the talents discussed as people with knowledge and skills who can create productivity and demonstrate excellent performance in individual fields, thereby enhancing national competitiveness.

2.2. *Cultivation and Utilization of Talents*

The effectiveness of talent cultivation and the benefits generated by the use of talents are closely related to the development of a country's industry, and they will also affect the competitiveness of a country. In the face of the rapid changes in the industrial environment and the development trend of the global market, successful cultivation and effective use of talents have become a topic that urgently needs attention in various countries. Research shows that countries with top economies are generally highly competitive, and governments in particular play a key role in shaping labor markets and talent competitiveness [15]. This study investigates the talent policies of top economies through literature in the hope of identifying key influencing factors. The talent policies of the top economies reveal that they believe that science, technology, engineering, and mathematics (STEM) are essential to increase productivity and strengthen national competitiveness [16–18]. This study referred to this discovery when selecting the input/output indicators of talent cultivation and utilization. Next, we selected the top three economies of the world for an introduction of the talent policies [19].

2.2.1. United States

Economically, the main reason why the United States is so strong, in addition to its rich natural resources, lies in the availability of top talent. In recent years, laws on talent cultivation and human resource planning issued by the United States have all been signed and passed by the President of the United States. This shows that the U.S. federal government attaches importance to talents and that talent cultivation policies and human resource planning have been upgraded to a national level [20]. President Trump signed the Strengthening Career and Technical Education for the 21st Century Act (Perkins V) into law in 2018. This bipartisan measure reauthorized the Carl D. Perkins Career and Technical Education Act of 2006 (Perkins IV) and continued the commitment of Congress to provide nearly USD 1.3 billion annually for career and technical education programs for the youth and adults. The need for science, technology, engineering, and mathematics (STEM) professionals has garnered global attention during the past two decades due to the significant role that these fields play in encouraging innovation, productivity, economic growth, and national security [16]. The need for STEM-prepared professionals has been highlighted by the ongoing COVID-19 pandemic, suggesting how important an adequate workforce with such capacities can be to a nation. As CoSTEM has emphasized, a well-equipped and "diverse talent pool of STEM-literate Americans prepared for future jobs will be essential for maintaining the national innovation base that supports key sectors of the economy" [17] (p. 6).

2.2.2. China

In China, the focus is to stimulate the creative vitality of talents for the 14th Five-Year period (2021–2025) through deepening the reform of the talent development mechanism, cultivating, introducing, and using talents in all directions, creating more world-class scientific and technological talents and innovative teams, as well as cultivating a pool of young scientific and technological talents with international competitiveness. They are working to improve the system for evaluating scientific and technological talents, deepen the reform of the academician system, improve the mechanism of innovation incentives and guarantees, build a profit distribution mechanism that fully reflects the value of elements for innovation such as knowledge and technology, and improve the rights and interests sharing mechanism of scientific research personnel's job invention achievements [21,22]. China emphasizes the cultivation of innovative, applied, and skilled talents and plans to grow a team of high-level engineers and highly skilled talents. They support the development of high-level research universities and strengthen the training of basic research talents. The Global Talent 2021 report by Oxford Economics predicted that by 2021, China will overtake the US as the country with the largest pool of educated talent [23].

2.2.3. Japan

In March 2019, the Ministry of Economy, Trade, and Industry (METI) of Japan announced a report on strengthening the competitiveness of Japanese companies [18]. According to this survey report, Japanese companies are currently facing the demand for innovation brought about by the trend of digitization, the diversified competition brought about by the trend of globalization, and the challenge of labor shortages caused by a declining birthrate and aging population, as well as the fact that they must prioritize the adjustment of human resource policies to further enhance its influence in the global industry. Facing the challenges of digitization, globalization, declining birthrates, and an aging population, the Japanese government actively encourages Japanese companies to use talent cultivation strategies to break the current situation of insufficient environments, mechanisms, and know-how. The talent cultivation strategy suggested by METI mainly focuses on four principles: (1) a hierarchical talent cultivation mechanism; (2) a flexible personnel salary system; (3) respect for personal corporate culture; (4) personnel departments corresponding to diversified needs. Among these, the hierarchical talent cultivation mechanism is regarded as crucial.

2.3. The NHRD System

In their national development strategies, countries are paying more and more attention to policies related to human resource development (HRD). The ability of a nation to develop human resources will become a competitive advantage for its long-term growth in the future, and this is academically known as national human resource development (NHRD). The definition and composition requirements of NHRD are not easy to determine because, at the national level, there is a complex interactive and dynamic relationship between NHRD and various stakeholders, including the main participants in the implementation of HRD plans, the scope of the activities involved, and specific countries [24–26]. Different factors, such as history, social background, and economic development stage, may change the definition and composition requirements of an NHRD; that is, each country has a suitable development of an NHRD system. Despite this, the goals are the same. They all hope to improve the knowledge and skills of individuals through the cultivation of talents and use these talents to increase productivity to promote national economic and social development.

In the last decades, there has been a growing interest in applying NHRD for economic growth and capacity building. However, much of the focus of NHRD has been on structures and delivery rather than on outcomes and performance evaluation [10]. The articles published on NHRD has increased and around 80% of the articles were published in HRD and training and development journals. Very few articles have been published in general management, international business, strategy, and organizational studies journals, indicating that research on NHRD is scarce in these fields [24,26]. According to our knowledge, our study is the first efficiency evaluation study regarding global NHRD systems.

Oh, Ryu, and Choi [7] proposed a conceptual model of NHRD to evaluate and assess the competitive advantage of a country's HRD system. The NHRD model consists of four factors, including demand conditions, supply conditions, environment, and supporting systems. It displays a measurement model of an NHRD system, including the three areas of acquiring, developing, and utilizing human resources.

Supply conditions refer to the acquisition and development of human resources to contribute to national economic and social development. According to human capital theory and related empirical research, there is a significant positive correlation between the improvement of competitiveness and the quantity and quality of human resources [27,28].

Demand conditions refer to the ratio of human resources cultivated through the national education system, used in the labor market, and other economic and non-economic incentive conditions. It includes attractive labor market conditions, the knowledge and skills (quality) of human resources, and the use (quantity) of human resources in the labor market. According to labor economics and human capital theory, the use of human resources in the labor market affects industrial competitiveness [29–31].

Support system refers to the investment activities in the NHRD system, as well as a national system that directly or indirectly invests in the acquisition, development, and use of human resources for a country. In addition to investing in tangible physical capital, intangible systems and systems also need attention [32,33]. The environment refers to the social conditions and infrastructure that affect the acquisition, development, and use of human resources. The environment exists outside of the supply and demand conditions but affects them. Oh et al. [7] argued that the environment comprises the following four sub-factors: technology, social capital, globalization, and industrial sophistication.

The operation of an NHRD system plays a decisive role in enhancing the country's competitiveness. A country must first improve the development of the various components of its NHRD system to form a sound system that can enhance the country's competitiveness. This study referred to the NHRD system model framework proposed by Oh et al. [7] as the basis for developing a two-stage NHRD system performance evaluation model. This process can be explained as follows. In the first stage, to obtain the talents with both quality and quantity (supply conditions aspects), a country needs to invest tangible resources, such as equipment, funds, or manpower. At the same time, corresponding talent development policies of the government must be formulated to assist talent cultivation and talent utilization (support system aspects). In the second stage, after acquiring talents, the country must also create an environment in which talents are willing to invest in the labor market (environment conditions aspects), enable talents to develop their strengths and create value, and ultimately achieve the goal of enhancing national competitiveness (demand conditions aspects).

2.4. Two-Stage DEA Models and Applications

The conventional DEA models neglect the structure of DMUs or internal operations. These models tend to over-evaluate the efficiency of system with complex internal structure [34] and lack discrimination power to distinguish between efficient units [35]. Inspired by the studies about multi-stage production process, Färe and Grosskopf [36] developed a general multi-stage model with intermediate inputs–outputs, commonly called "network DEA". Most scholars [37,38] agree that network DEA has three major advantages: (1) the models can simulate the internal structure of system, and the efficiencies of sub-DMUs and the overall efficiency of system can be evaluated simultaneously; (2) the network DEA proposes and proves the divisibility of the overall efficiency of system with complex internal structure, and the calculation can reduce the number of efficiency DMU; (3) the method provides the possibility to study the resource allocation within the system and to explore the relationship among the sub-DMUs. For more general situations, an extension of the network DEA model introduced by Tone and Tsutsui [39] can be applied via the SBM (slacks-based measure) technique. Fukuyama and Weber [40] extended the SBM network

DEA model for cases involving undesirable outputs. These network DEA models have been widely applied to various fields.

Generally, the sub-DMUs in series and sub-DMUs in parallel are the two most common cases in the description of DMU's internal structure by the network DEA approach [38]. Taking the two-stage system as an example, the serial structure assumes that each system is comprised of two sub-stages connected in series, wherein the first stage consumes the external inputs to produce intermediate measures which are used by the second stage to produce the final outputs. Kao and Hwang [41] defined the overall efficiency of such a system as the product of the efficiency ratios of stages 1 and 2. The multiplicative method is used by many scholars (e.g., [42,43]) to evaluate and decompose the efficiency of the system within which there are two sub-DMUs connected in series. However, the parallel structure considers that the internal structure of a two-stage system is composed of two independent sub-stages in parallel, and the sum of the inputs or outputs of each stage is the inputs or outputs of the whole system. Bi et al. [44] also dealt with organization consisting of several production units, each of which has parallel production lines. Kao [45] applied the additive approach to evaluate and decompose the Malmquist productivity index for parallel production systems.

This is to say that the multiplicative efficiency decomposition method underlines the link role of the intermediate measures between two stages, while the additive method emphasizes the relative contribution of the efficiency of each stage to the performance of whole system. However, the serial system proposed by Kao [46] is a "closed system", wherein the outputs from one stage become the inputs to the next stage, and where no other inputs enter the sub-DMUs at any intermediate stage [47]. Based on these studies, Kao [48] proposed a DEA approach to evaluate and decompose the efficiency of general multi-stage systems with consideration of exogenous inputs and intermediate products for each stage.

Moreover, measuring the performance can be challenging when inputs and outputs are shared among different processes and are not easily distinguished [49]. Yu and Shi [50] examined a two-stage structure with additional inputs in the second stage and some of the intermediate products as final outputs, towards building cooperative and leader–follower models. Halko et al. [51] surveyed and classified the two-stage DEA models and presented the applications of these models across the literature. Ma et al. [38] proposed a parallel-series hybrid two-stage DEA model utilizing the principles of additive and multiplicative efficiency decomposition.

In conclusion, the standard single-stage DEA approach is a valuable tool for efficiency evaluation; however, when there are more complex systems than a simple input–output procedure, it fails to address the internal structures. Considering the processes of talent development and the properties of an NHRD system, the sub-DMUs in series (i.e., the serial structure) in the study will be more appropriate to evaluate the efficiency at present.

3. Research Design

3.1. Research Framework

Currently, in most performance analyses and evaluations, the multi-index framework is used. This framework may also be combined with quantitative and qualitative indexes. The traditional DEA model neglects the connectivity and context between various activities in the system—it treats each DMU as a "black box" when measuring the input–output efficiency; consequently, they cannot effectively present potential information and the managerial implications [11]. Therefore, to overcome the above problems, we established a two-stage efficiency measurement model using the DEA method as the performance evaluation tool for NHRD systems. Based on the above description, this study re-examined the definition of an NHRD system by integrating the studies of Oh et al. [7] and Chung [52] and argued that to evaluate the performance of an NHRD system clearly, it is necessary to consider not only the cultivation efficiency of talents but also the utilization efficiency of talents that create added value for countries, in order to more integrally present the information and implication of NHRD systems concerning operation and management. We further analyzed multiple factors affecting the staged operations of the system, so that it could serve as a reference for the future improvement and perfection of NHRD systems. Figure 1 shows the details of the model in the paper.

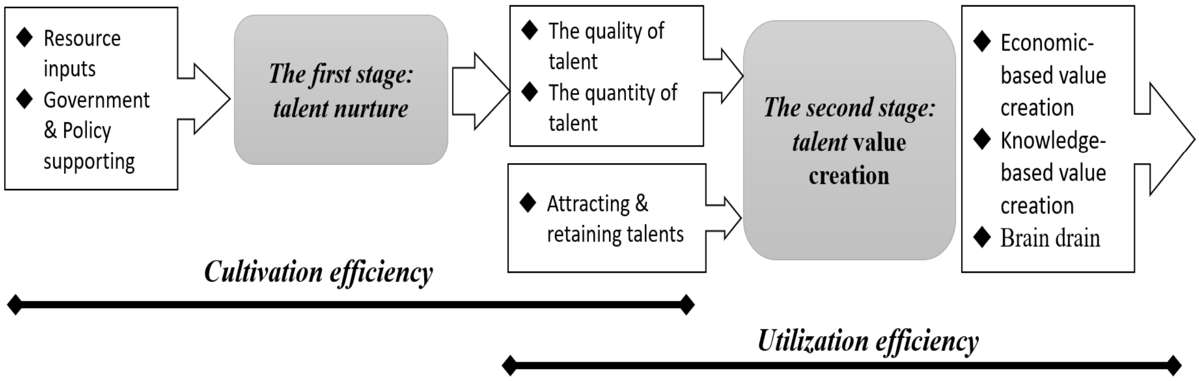

Figure 1. Two-stage process efficiency model of the NHRD system.

This study constructed a two-stage data envelopment analysis model to evaluate the efficiency of the talent cultivation and talent utilization of NHRD systems in various countries from the perspective of HRD. In addition, considering the problem of brain drain, bad output (i.e., brain drain) was incorporated into the model. The study subjects comprised 60 countries, including Argentina, China, and OECD member countries. Finally, this study found that countries that are proficient at nurturing talents do not necessarily have the ability to use talents to create value effectively. In addition, a sensitivity analysis was also conducted in this study to identify important input indexes that affect the talent cultivation and utilization efficiency, which could be used as a reference for NHRD system efficiency improvement in various countries.

3.2. Selection of Input and Output Variables

3.2.1. The First Stage: The Evaluation of the Efficiency of Talent Cultivation

In terms of the inputs in the first stage, in addition to basic production factors, talent cultivation also requires the cooperation of government and support in terms of policies. Therefore, this study divided the inputs into resource inputs and government and policy support. For the resource inputs, three variables were selected: total public expenditure on education per capita (EDU), total spending on R&D (RDG), and science in education schools (SIS). For government and policy support, three variables were also selected: educational system (ES), equal opportunity (EO), and employee training and apprenticeship (ETA).

In terms of the outputs in the first stage, to cultivate talents who can meet the needs of the economic environment, besides the pursuit of quantity, quality should also be emphasized. Therefore, this study divided the output indicators into two parts: the quantity and the quality of talents. Quantity represented the number of talents cultivated by the country, while quality represented whether the talents have the competitiveness required by the environment of the times. In terms of quantity, three variables were selected: skilled labor (SL), finance skills (FS), and competent senior managers (CSM). In terms of quality, three variables were also selected: university education (UE), management education (ME), and language skills (LS).

3.2.2. The Second Stage: The Evaluation of the Efficiency of Talent Utilization

Considering the inputs in the second stage, the outputs from the first stage were the main focus, while attracting and retaining talents (ART) was added as a variable to represent the concept of acquiring human resources in the NHRD system proposed by Oh et al. [7]. Acquiring human resources is not an easy process, and putting the right people in the right places can be even more challenging. This variable was used to examine whether the business environment of a country has sufficient incentives to make talents willing to invest in that country's market and whether their system can efficiently retain talents and enable talents to display their value. Therefore, the study has only two stages of developing and utilizing human resources, and acquiring human resources was replaced as an input variable and included in the second-stage efficiency assessment.

Considering the outputs in the second stage, each variable/indicator represents the value that can enhance or create a country's competitiveness. In this study, the outcomes of the second stage were divided into two parts: economics-based value creation and knowledge-based value creation. For knowledge-based value creation, two variables were selected: scientific research (SR) and the number of patents in force (PATT). For the economic outputs, two variables were also selected: overall productivity (OP) and high-tech exports (HTEX). In addition to value creation, we also considered the problem of a country's failure to effectively use talents and losing value. In other words, the root cause of brain drain (BD) is that talent cannot be used or used improperly in the country (i.e., no employment prospects or lack of job security). BD has been shown to affect the sustainability of domestic businesses and the overall economic development [53]. Therefore, the non-intended output variable of BD was included in the outputs. The input and output variables are summarized in Table 1.

The samples mainly included OECD members, but also included BRIC countries such as China, Brazil, and Russia. After eliminating the countries with incomplete data, there were finally 60 countries. Variable data sources included the Government Finance Statistics Yearbook (GFSY) 2013 [54], the OECD Main Science and Technology Indicators [55], the World Talent Report (WTR), and the World Competitiveness Yearbook (WCY), both issued by the Institute for Management Development IMD [56] between 2014 and 2017, the WIPO Statistics Database [23], the Conference Board Total Economy Database [57], and World Bank Open Data [58].

Table 1. Explanation of input and output variables of the NHRD system.

Variable	Definition (Unit)	Sources and Time of Data Generation
Inputs of stage-1:		
EDU	Total public expenditure on education per capita (USD per capita).	2013 data from IMF [54]
RDG	Total expenditure on R&D (percentage of GDP).	2013 data from OECD—Main Science and Technology Indicators [55]
SIS	Science in schools. Whether science education in schools is sufficiently emphasized (survey 0–10).	2014 data from WTR [59]
ES	Educational system. The educational system meets the needs of a competitive economy (survey 0–10).	2014 data from WTR [59]
EO	Equal opportunity. Whether the equal opportunity legislation in your economy encourages economic development (survey 0–10).	2014 data from OECD—Main Science and Technology Indicators [55]
ETA	Employee training and apprenticeships. Employee training is a high priority in companies (survey 0–10) and apprenticeship is sufficiently implemented (survey 0–10).	2014 data from WTR [59]
Intermediate outputs:		
SL	Skilled labor. Skilled labor is readily available (survey 0–10)	2015 data from WTR [56]
FS	Finance skills. Whether finance skills are readily available (survey 0–10).	2015 data from WTR [56]
CSM	Competent senior managers. Competent senior managers are readily available (survey 0–10).	2015 data from WTR [56]
UE	University education. University education meets the needs of a competitive economy (survey 0–10).	2015 data from WTR [56]
ME	Management education. Management education meets the needs of the business community (survey 0–10).	2015 data from WTR [56]
LS	Language skills. Whether language skills meet the needs of enterprises (survey 0–10).	2015 data from WTR [56]

Table 1. *Cont.*

Variable	Definition (Unit)	Sources and Time of Data Generation
Inputs of stage-2:		
ART	Attracting and retaining talents. Whether attracting and retaining talents is a priority in companies (survey 0–10).	2015 data from WTR [56]
Final outputs		
SR	Scientific research. The public and private scientific research are high by international standards (survey 0–10).	2016 data from Web of Science
PATT	Number of patents in force (per 100,000 inhabitants).	2016 data from WIPO Statistics Database [23]
OP	Overall productivity (USD).	2017 data from The Conference Board—Total Economy Database [57]
HTEX	High-tech exports (%).	2016 data from World Bank Open Data [58]
BD	Brain drain. Whether the well-educated and skilled people do not hinder competitiveness in the economy of the country (survey 0–10).	2017 data from WTR [15]

PS: ETA (employee training and apprenticeships) is the average of ET and apprenticeship in the IMD report.

Talent development activities are a continuous process, so the effect of time-lag must be considered when constructing evaluation models. Some studies have pointed out that considering the time-lag effect between input and output is one of the important factors to improve the validity of assessment [11,18]. However, when DEA or network DEA was used as the performance measurement model, each input and output was set as the same period of activity, which may be in line with the factory production unit, but in the cultivation and utilization of talents, a longer delay needs to be considered to conform to the relationship between input and output in the actual field, it can also avoid distortion or overestimation of performance measurement. Therefore, considering that there was a delay, there was a time gap of at least one year between the inputs and outputs by time of data generation. The evaluation period was from 2013 to 2017, for a total of five years.

3.3. Methodology

Slacks-Based Measure (SBM) on the Undesirable Outputs Model

Data envelopment analysis (DEA) was first proposed by Charnes et al. [60] as a non-parametric approach to estimate the relative efficiency of a DMU. Since then, many studies have used it and published on its methodology and applications in various areas, such as education, agriculture, healthcare, and the banking industry [61,62]. The DEA is widely acknowledged for its strength in capturing multiple inputs and outputs, computing performance measures that integrate data/information across multiple dimensions and input/output resources, and combining multiple performance dimensions [63]. The two types of DEA models include radial and non-radial models. As the radial efficiency CCR and BCC models assume that the inputs and outputs increase or decrease in equal proportions, slacks still exist; our model dealt with this problem by applying the slacks-based measure of efficiency (SBM) of Tone [64]. SBM is non-oriented and non-radial, utilizing input and output slacks directly in producing an efficiency measure. In our model, SBM was modified to account for undesirable outputs.

Let us decompose output matrix Y into (Y^g, Y^b), where Y^b and Y^g denote bad (undesirable) and good (desirable) output matrices, respectively. For a DMU $(x_o,\ y_o)$, the decomposition is denoted as $\left(x_o, y_o^g, y_o^b\right)$. We consider the production possibility set defined by

$$P = \left\{ \left(x, y^g, y^b\right) \middle| x \geq X\lambda,\ y^g \leq Y^g\lambda,\ y^b \geq Y^b\lambda, L \leq e\lambda \leq U, \lambda \geq 0 \right\} \quad (1)$$

where λ is the intensity vector, and L and U are the lower and upper bounds of the intensity vector, respectively. The efficiency status in this framework is defined as follows:

A DMU $\left(x, y^g, y^b\right)$ is efficient in the presence of bad outputs if there is no vector $\left(x, y^g, y^b\right) \in P$, such that $x_o \geq x,\ y_o^g \leq y^g,\ y_o^b \geq y^b$, with at least one strict inequality.

In accordance with this definition, we modified the SBM of Tone [64] as follows:

$$\rho^* = \min \frac{\left(1 - 1/m \sum_{i=1}^{m} \frac{s_{io}^-}{x_{io}}\right)}{1 + 1/s\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{ro}^b}\right)} \tag{2}$$

s.t. $x_o = X\lambda + s^-$
$y_o^g = Y\lambda - s^g$
$y_o^b = Y\lambda + s^b$
$L \leq e\lambda \leq U$
$s^-, s^g, s^b, \lambda \geq 0$

The vectors s^b and s^- correspond to excesses in the bad outputs and inputs, respectively, while s^g expresses shortages in the good outputs. s^1 *and* s^2 denote the number of elements in s^b *and* s^g and $s = s_1 + s_2$. Let an optimal solution of the above program be $\left(\rho^*,\ s^{-^*},\ s^{g^*}, s^{b^*}\right)$; we can then demonstrate that the DMU $\left(x_o, y_o^g, y_o^b\right)$ is efficient in the presence of undesirable outputs if and only if $\rho^* = 1$, *i.e.*, $s^{-^*} = 0,\ s^{g^*} = 0, s^{b^*} = 0$. If the DMU is inefficient, i.e., $\rho^* < 1$, it could be improved and become efficient by deleting the excesses in the bad outputs and inputs and augmenting the shortfalls in the good outputs by the following projection:

$$\begin{aligned} x_o &\Leftarrow x_o - s^{-^*} \\ y_o^g &\Leftarrow y_o^g + s^{g^*} \\ y_o^b &\Leftarrow y_o^b - s^{b^*} \end{aligned} \tag{3}$$

The above fractional program can be transformed into an equivalent linear program by using Charnes–Cooper transformation (see [64] for details). By considering the dual side of the linear program, we have the following dual program in the variable $v,\ u^g,\ u^b$ for the constant returns to scale (CRS) case (SBM-CCR efficiency), i.e., $L = 0,\ U = \infty$; for the variable return to scale (VRS) case (SBM-BCC efficiency), i.e., $L = 1,\ U = 1$ (refer to [64] for derivation.)

$$\max\ u^g y_o^g - v x_o - u^b y_o^b \tag{4}$$

s.t.
$u^g Y^g - vX - u^b Y^b \leq 0$
$v \geq \frac{1}{m}[1/x_o]$
$u^g \geq \frac{1 + u^g y_o^g - v x_o - u^b y_o^b}{s}\left[1/y_o^g\right]$
$u^b \geq \frac{1 + u^g y_o^g - v x_o - u^b y_o^b}{s}\left[1/y_o^b\right]$

The dual variables v and u^b can be interpreted as the virtual prices (costs) of inputs and bad outputs, respectively, while u^g denotes the price of good outputs. The above dual program aims at obtaining the optimal virtual costs and prices for the DMU so that the profit $u^g y^g - vx - u^b y^b$ does not exceed zero for every DMU and maximizes the profit $u^g y_o^g - v x_o - u^b y_o^b$ for the DMU concerned. Apparently, the optimal profit is at best zero and this identifies the DMU as efficient.

Using both VRS and CRS output-oriented models, the relative efficiency of the NHRD system has been measured (i.e., BBC score and CCR score). Regarding the input-output orientation of the model, according to [65], the choice should be based on the market conditions of the DMUs. As a general rule of thumb, in competitive markets, DMUs are output oriented, since it is assumed that inputs are under control of the DMU, which aims to maximize its output subject to market demand. Therefore, we chose output orientation for our DEA model (SBM on the undesirable outputs model).

The objective of this paper was to investigate efficiency decomposition in a two-stage production process where the outputs of the first stage are the inputs of the second stage.

Mathematically, for additional details on the DEA model the reader can refer, for example, to Kao and Hwang [41] or Carayannis et al. [66].

4. Empirical Results

This study used DEA-Solver version 15.2 to evaluate talent cultivation and talent utilization efficiency in 60 countries, including the United States, China, the United Kingdom, and several developing countries. First, we solved the technical efficiency (TE) and pure technical efficiency (PTE) of each country through the CCR and BCC models of the SBM (undesirable) output-oriented model in the two stages. Then, TE was divided by PTE to find the scale efficiency (SE) to determine the potential sources of the overall inefficiency and technical inefficiency at each stage. Following this, sensitivity analysis was conducted to explore the influence of the input variable on the efficiency vibration by removing it.

Before performing the efficiency analysis, it was necessary to confirm whether there was an isotonic relationship between the selected input variable and the outputs. For this, we followed previous studies and used the Pearson correlation coefficient to test each input–output variable [67,68]. The results showed that at least one pair of input–output variables had a significantly positive correlation and that the bad outputs of the second stage were all significantly negative, in line with the assumption of isotonicity.

4.1. Efficiency Analysis

In DEA, when the efficiency value of the DMU is 1, the DMU has relative efficiency; if the efficiency value is less than 1, the DMU is relatively inefficient. The analysis results of this study are shown in Table 2. In the first stage of talent cultivation efficiency, the average of TE was 0.833. A total of 21 countries out of the 60 evaluated countries showed relative efficiency, including Belgium, New Zealand, the USA, and Israel. In the second stage of talent utilization efficiency, the average of TE was 0.521. Sixteen countries showed relative efficiency, including Denmark, Finland, and Germany. It was apparent that in most European countries, the talent utilization efficiency is better than the talent cultivation efficiency. Only three countries showed overall efficiency (OE) (i.e., relatively efficient in both stages), namely, Bulgaria, the Philippines, and the USA. Overall, the efficiency of talent cultivation is better than the efficiency of utilization, indicating that around the world, countries generally pay more attention to the establishment and development of abundant talent pool resources; however, it is easy to neglect how to effectively use talents after nurture or acquisition.

Table 2. Overall efficiency and stage efficiency decomposition.

Country (DMU)	Overall Efficiency [1]	First Stage: Cultivation eff.				Second Stage: Utilization eff.			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
Austria	0.687	0.679	0.848	0.801	DRS	0.695	1.000	0.695	IRS
Belgium	0.799	1.000	1.000	1.000	CRS	0.639	0.817	0.782	IRS
Bulgaria	1.000	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
Croatia	0.434	0.677	0.683	0.992	IRS	0.278	1.000	0.278	IRS
Czech Republic	0.495	0.883	0.887	0.995	DRS	0.277	0.480	0.578	IRS
Denmark	0.757	0.720	1.000	0.720	DRS	0.796	0.878	0.908	IRS
Estonia	0.725	0.526	0.660	0.797	DRS	1.000	1.000	1.000	CRS
Finland	0.666	0.716	1.000	0.716	DRS	0.619	0.765	0.810	IRS
France	0.799	0.639	0.733	0.872	DRS	1.000	1.000	1.000	CRS
Germany	0.849	0.762	1.000	0.762	DRS	0.947	1.000	0.947	IRS
Greece	0.422	1.000	1.000	1.000	CRS	0.178	0.378	0.472	IRS
Hungary	0.464	0.606	0.614	0.987	DRS	0.356	1.000	0.356	IRS
Iceland	0.642	0.830	0.970	0.856	DRS	0.496	0.782	0.634	IRS
Ireland	0.794	0.630	1.000	0.630	DRS	1.000	1.000	1.000	CRS
Italy	0.725	1.000	1.000	1.000	CRS	0.525	1.000	0.525	IRS
Latvia	0.472	0.830	0.923	0.899	DRS	0.268	0.436	0.615	IRS

Table 2. *Cont.*

Country (DMU)	Overall Efficiency [1]	First Stage: Cultivation eff.				Second Stage: Utilization eff.			
		TE	PTE	SE	RTS	TE	PTE	SE	RTS
Lithuania	0.412	0.771	1.000	0.771	DRS	0.220	0.322	0.681	IRS
Luxembourg	0.855	0.731	1.000	0.731	DRS	1.000	1.000	1.000	CRS
Netherlands	0.800	0.794	1.000	0.794	DRS	0.807	0.999	0.808	IRS
Norway	0.920	0.846	1.000	0.846	DRS	1.000	1.000	1.000	CRS
Poland	0.379	0.911	1.000	0.911	DRS	0.158	1.000	0.158	IRS
Portugal	0.497	1.000	1.000	1.000	CRS	0.247	1.000	0.247	IRS
Romania	0.346	1.000	1.000	1.000	CRS	0.120	0.203	0.593	IRS
Slovak Republic	0.469	0.750	0.822	0.913	DRS	0.293	1.000	0.293	IRS
Slovenia	0.657	0.825	0.829	0.996	DRS	0.523	1.000	0.523	IRS
Spain	0.699	1.000	1.000	1.000	CRS	0.488	1.000	0.488	IRS
Sweden	0.868	0.871	1.000	0.871	DRS	0.865	0.999	0.865	IRS
Switzerland	0.877	0.769	1.000	0.769	DRS	1.000	1.000	1.000	CRS
Ukraine	0.410	1.000	1.000	1.000	CRS	0.168	0.999	0.168	IRS
United Kingdom	0.878	0.771	1.000	0.771	DRS	1.000	1.000	1.000	CRS
China	0.628	0.778	0.918	0.847	DRS	0.507	1.000	0.507	IRS
Hong Kong	0.752	1.000	1.000	1.000	CRS	0.565	0.676	0.836	IRS
India	0.200	1.000	1.000	1.000	CRS	0.040	0.096	0.420	IRS
Indonesia	0.047	0.746	0.822	0.908	DRS	0.003	0.012	0.281	IRS
Israel	0.822	1.000	1.000	1.000	CRS	0.675	0.999	0.676	IRS
Japan	0.647	0.418	0.557	0.750	DRS	1.000	1.000	1.000	CRS
Jordan	0.135	0.830	0.838	0.991	DRS	0.022	0.169	0.132	IRS
Kazakhstan	0.519	0.864	0.899	0.961	DRS	0.312	0.473	0.659	IRS
Korea	0.840	0.706	0.812	0.871	DRS	1.000	1.000	1.000	CRS
Malaysia	0.500	0.717	1.000	0.717	DRS	0.349	0.349	1.000	IRS
Philippines	1.000	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
Qatar	0.837	0.701	0.790	0.887	DRS	1.000	1.000	1.000	CRS
Russia	0.524	0.770	0.826	0.932	DRS	0.356	0.999	0.357	IRS
Singapore	0.865	0.748	1.000	0.748	DRS	1.000	1.000	1.000	CRS
Taiwan	0.808	0.653	0.828	0.789	DRS	1.000	1.000	1.000	CRS
Thailand	0.220	0.754	0.792	0.953	DRS	0.064	0.999	0.064	IRS
Turkey	0.370	0.707	1.000	0.707	DRS	0.194	0.318	0.611	IRS
UAE	0.868	0.753	1.000	0.753	DRS	1.000	1.000	1.000	CRS
Argentina	0.230	1.000	1.000	1.000	CRS	0.053	0.999	0.053	IRS
Brazil	0.265	0.644	0.667	0.966	DRS	0.109	0.999	0.109	IRS
Canada	0.644	0.851	1.000	0.851	DRS	0.488	0.633	0.770	IRS
Chile	0.423	1.000	1.000	1.000	CRS	0.179	0.999	0.179	IRS
Colombia	0.373	1.000	1.000	1.000	CRS	0.139	0.815	0.171	IRS
Mexico	0.308	1.000	1.000	1.000	CRS	0.095	0.442	0.214	IRS
Peru	0.118	1.000	1.000	1.000	CRS	0.014	0.998	0.014	IRS
South Africa	0.470	1.000	1.000	1.000	CRS	0.221	0.656	0.338	IRS
USA	1.000	1.000	1.000	1.000	CRS	1.000	1.000	1.000	CRS
Venezuela	0.164	1.000	1.000	1.000	CRS	0.027	0.133	0.204	IRS
Australia	0.636	0.807	1.000	0.807	DRS	0.501	0.689	0.728	IRS
New Zealand	0.608	1.000	1.000	1.000	CRS	0.370	0.770	0.480	IRS
Average score	0.594	0.833	0.929	0.897		0.521	0.805	0.620	

[1] Overall efficiency (OE) = geometric mean (TE of cultivation andTE of utilization).

PTE analysis measures whether a DMU can effectively use resources to minimize input or maximize output without considering the scale efficiency. The analysis results are presented in Table 2. In the first stage of talent cultivation efficiency, the average PTE was 0.929. A total of 39 countries of the 60 evaluated countries showed high PTE, indicating that 65% of the countries can effectively use input resources to create a talent pool for the country. In the second stage of talent utilization efficiency, the average PTE was 0.805. Twenty-seven countries achieved the best PTE, indicating that less than half of the countries (45%) can effectively use the talents created to generate economic or intellectual value for the country. Furthermore, 15 countries had high PTE in both stages, indicating that only

25% of the 60 evaluated countries can effectively use the invested resources to create talent resources and effectively use the created talent resources.

By dividing the TE by the PTE, the scale efficiency (SE) could be calculated. From this, we were able to find out the source of the TE inefficiency (whether it comes from the PTE-inefficiency or the SE-inefficiency). In DEA, when the SE of a DMU is 1, it means the DMU is in a state of the most suitable return to scale (RTS), that is, constant returns to scale (CRS); on the contrary, less than 1 value of SE means the DMU has inefficient SE, and its RTS may have decreasing returns to scale (DRS) or increasing returns to scale (IRS) [69]. SE measures whether the RTS of a DMU is appropriate. If the DMU is in a DRS state, streamlining its resource input scale is recommended; if the DMU is in an IRS state, its scale should be appropriately expanded. The analysis results are shown in Table 2. In the first stage of talent cultivation, the SE average was 0.897. A total of 21 countries out of the 60 evaluated countries reached the SE efficiency. In the SE-inefficient countries, other than Croatia (which was IRS), the remaining 38 countries were all DRS. These countries can reduce their investment in resources to reduce their cultivation scale. In addition, the SE average in the talent utilization stage was 0.620, and 17 of the 60 evaluated countries had efficient SE. The countries with inefficient SE all had IRS. These countries are suggested to increase their input resources to expand their RTS in the utilization stage. Overall, the SE of talent cultivation was better than the SE of talent utilization.

The source analysis of inefficiency is shown in Table 3. Comprehensive observations and comparisons of the average values for TE, PTE, and SE in the two stages revealed that (1) the primary source of the overall inefficiency was talent utilization inefficient, i.e., in relative terms, the efficiency of talent cultivation (0.833) was higher than the efficiency of talent utilization (0.521); (2) the primary source of the TE inefficiency in the two stages was both SE inefficiency, i.e., the PTE (0.929 and 0.805) was higher than the SE (0.897 and 0.621) in the two stages; (3) in the first stage, most countries with inefficient SE (38 countries, 97%) had DRS, suggesting that on increasing the scale of inputs, the input–output benefit will be lower than the current benefit. On the contrary, in the second stage, all countries with inefficient SE (43 countries, 72%) had IRS, suggesting that if the scale of inputs is increased, the input–output benefit is higher than the current benefit. On the whole, the reason for the inefficiency of OE was the inefficiency of scale; among these, most countries with inefficient scale in the first stage were observed to be in a state of DRS, and countries with inefficient scale in the second stage were all in the state of IRS.

Table 3. The source analysis of inefficiency.

	Overall Efficiency (OE)	**First Stage: Talent Cultivation**				**Second Stage: Talent Utilization**			
		TE	**PTE**	**SE**	**DRS**	**TE**	**PTE**	**SE**	**IRS**
Average score	0.594	0.833	0.929	0.897		0.521	0.805	0.620	
No. of efficient DMUs		21	39	21	38	16	27	16	44

4.2. Sensitivity Analysis

The sensitivity analysis of the input variables/indicators of the two stages is shown in Table 4. ETA was the most sensitive to the PTE, indicating that this variable is the most important to the PTE of talent cultivation. Countries can prioritize improvements from the input ETA to improve the efficiency of talent cultivation. In the second stage, ART was the most sensitive to the PTE, showing that this variable is the most important to the PTE of talent utilization. It is recommended that countries prioritize improvements from adjusting the input–output ratio of ART to improving the efficiency of talent utilization.

Table 4. The sensitivity analysis of the input variables.

Stage **PTE Score (Original)**	**First Stage**	**0.929**	**Difference**	**Rank**	**Second Stage** **0.805**	**Difference**	**Rank**
Input for removal	EDU	0.916	0.013	3			
	RDG	0.915	0.014	2			
	SIS	0.918	0.011	4			
	ES	0.920	0.009	5			
	EO	0.921	0.008	6			
	ETA	0.911	0.018	1			
	SL				0.785	0.020	3
	FS				0.775	0.030	2
	CSM				0.800	0.005	6
	UE				0.803	0.002	7
	ME				0.799	0.006	5
	LS				0.798	0.007	4
	ART				0.664	0.141	1

5. Conclusions and Implications

Different from the traditional one-stage DEA model, this study constructed a two-stage DEA model from the perspective of process efficiency to examine more comprehensively the overall picture of countries that enhance their national competitiveness through talents. The results could allow relevant countries to understand their own position of talent efficiency and the gap with other countries and be used as a reference for countries to formulate, implement, and review relevant talent policies.

The results showed that the efficiency of talent cultivation is relatively better than the efficiency of talent utilization in various countries, and that countries with good talent cultivation efficiency do not necessarily have talent utilization efficiency. In the first stage, the TE average was 0.833, and 21 countries achieved TE efficiency; however, the TE average in the second stage was only 0.521, and the number of countries reaching TE efficiency was reduced to 16. This indicated that all countries are aware of the importance of talents in promoting the economy and enhancing a country's competitiveness and have spared no effort in establishing national talent pools, putting forward various policies or programs to cultivate, attract, recruit, and retain talents [70]. However, after acquiring talents, the way in which to effectively use talents and make them effective is generally ignored. As a result, although there are many outstanding talents, they cannot provide the value of creating competitiveness.

Second, the results showed that the primary reason for the inefficiency of talent cultivation and talent utilization in various countries is the inefficiency of scale. Most countries with scale inefficiency in the first stage were in a DRS state, while countries with scale inefficiency in the second stage were in an IRS state. In the first stage of talent cultivation, 39 of the 60 countries had not reached the optimal cultivation scale. As most of the countries were in a state of DRS, countries are suggested to re-examine the allocation of input resources and make the design and operation of the cultivation system meet the target/needs of the country's economic development. In the second stage of talent utilization, 44 of the 60 countries had not yet reached the optimal utilization scale, and these countries were in a state of IRS. It is thus recommended that these countries increase the talent resources that meet the needs of national development and create high-value job opportunities to expand the talent utilization scale.

Third, in terms of the sensitivity analysis, the most important indicator/factor affecting the efficiency of talent cultivation was employee training and apprenticeships (ETA). Therefore, it is suggested that when there is a limit to improving the efficiency and resources, countries directly start with raising the resource input of this indicator. Compared with the investment of human, material, or financial resources, these findings indicate that a suitable training system is more important for talent cultivation. This also echoed the results of the ManpowerGroup 2018 Talent Shortage Survey [71]. To effectively reduce the learning gap or knowledge gap and cultivate more high-quality talent resources that can meet market needs, it is necessary to formulate policies to increase professional education and vocational training. Furthermore, the most important factor affecting the efficiency of talent utilization in the second stage was attracting and retaining talents (ART). This indicator examines whether the business environment of a country has enough incentives to make talents willing to stay in the market and whether a country has a good system that can retain talents and make talents show their value [56]. Therefore, active strengthening of the policy of recruiting talents is recommended, improving the quality of life in the country, enhancing the environment for retaining talents, and increasing the attractiveness of foreign technical talents to help improve the efficiency of talent utilization in a country.

Several implications and future research directions follow: The findings of the study have shown that the efficiency of talent cultivation is relatively better than the efficiency of talent utilization in various countries. From a perspective of intellectual capital [72], people are the main body of knowledge, so knowledge needs to be selected, absorbed, used, refined, innovated, and disseminated by people in order to exert its value. If the country can effectively integrate intellectual capital with knowledge management built to achieve expected results, creating an environment where talents are able and willing to play their strengths will increase the value cycle process of intellectual capital, improve the effectiveness of talents to create value, and then drive the progress of the country. Therefore, the way in which to effectively integrate the perspective of intellectual capital with the NHRD system is a future study.

Talent is the key factor to enhance national competitiveness. The importance of talents is now more important than before. Therefore, it is necessary to establish a performance evaluation model that can examine the effectiveness of national talent cultivation and utilization. In terms of the selection of DMUs, this study took 60 countries covering Asia, Europe, America, and Oceania as the evaluation objects and conducted a wide range of discussions. It is suggested that follow-up research can only focus on one continent for a more in-depth discussion.

In terms of model construction, follow-up research should use different methods to collect input–output indicators and establish models based on relevant theories, such as expert interviews, brainstorming methods, or the modified Delphi method, to discuss more completely and improve the validity of the evaluation.

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