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The Nexus of FDI, R&D, and Human Capital on Chinese Sustainable Development: Evidence from a Two-Step Approach

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Abstract: This study examines the effect of the foreign direct investment (FDI)–human capital and R&D–human capital interactions (FDIHC and RDHHC) on Chinese development between 1991 and 2015. Based on endogenous growth theory, the study focuses on FDI, R&D, and human capital as important factors for sustained economic growth; the interactions among factors are set as the main variables affecting economic growth (GDP). In particular, this study attempts a two-step empirical analysis. First, data mining and semantic network analysis (SNA) are performed using variables as keywords; reliability and realism are reflected as variables. Second, using the vector error correction model (VECM), the study analyzes short and long run mutual influences between variables. The results show that, in data mining and SNA with FDI and R&D as keywords, words related to human capital show high frequency, centrality, and clustering. This finding implies that FDIHC and RDHHC have robustness as variables and can be used as interaction variables. According to the VECM results, FDIHC and RDHHC have positive influences on GDP in the short and long run. The results of a variance decomposition test show that RDHHC has strong mid- to long-run impacts on GDP, FDIHC, and R&D itself.

Keywords: FDI-human capital; R&D-human capital; vector error correction model; text mining; semantic network analysis; Chinese economic growth

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1. Introduction

A country can realize change and development through sustainable investment, and many countries have focused on foreign direct investment (FDI) and R&D for social advancement [1]. FDI isusually considered to be the most effective means of early-stage national economic development, whereas R&D investment is recognized as an indispensable factor for sustainable development in host countries [2]. FDI can play a positive role in a host country's economic development by transferring the beneficial capital, advanced technology, management know-how, and intangible assets of an enterprise [3,4]. R&D, as an essential factor in enhancing national competitiveness and sustainable development, emphasizes intangible assets and soft power in the process of economic development [5–9]. Thus, sustainable development places importance on the dynamics of FDI, R&D, and soft power, such as human capital. In particular, human capital is a fundamental element of endogenous growth theory. It is categorized as a crucial factor that affects national development along with growth promotion factors like FDI and R&D. Furthermore, human capital can play a key role in maintaining a nation's sustainable development in combination with other growth drivers. The interaction between FDI and human capital therefore entails not only pure capital inflow but also the human capital quality of the host country to which advanced knowledge and technology are introduced for acceptance [10]. In the context of R&D, human capital leads to creative and developmental outcomes from the use of new knowledge and technology. In other words, research on national sustainable development should reveal the impact of each factor (FDI or R&D) on growth, as well as the impacts of interactions with other factors on growth. As a result, in-depth research on the sustainable growth of a country needs to take into account both causal and interrelated dimensions.

For this analysis, I designate China as the country that can most effectively demonstrate the theoretical context of this development theory. China is the second largest economy in the world to absorb FDI after the US, and it is the largest destination for FDI among developing countries [11]. In China, FDI has brought not only the capital but also the high-level intangible assets of advanced countries, such as, for example, advanced technology, marketing know-how, distribution management, organizational management, customer management, and so on [3,4,12]. As a result, in addition to contributing to domestic capital formation, the creation of employment, and economic growth, FDI can also generate human capital growth and R&D investment for domestic firms [13]. These two factors, shaped by FDI, have been synergizing Chinese development through continuous interactions between FDI, R&D, and human capital. Despite the fact that the correlations and interactions between these factors have substantial impacts on China's development, many researchers to date have also focused on the independent impacts of FDI, R&D, and human resources on Chinese economic growth [14–21]. To overcome this limitation, I explore how the interaction effects of FDI–human capital and R&D–human capital—factors that are critical for sustainable development in developing countries—have affected Chinese economic growth.

Unlike other similar studies, this study is unique in the following ways. First, I diversify variables based on literature reviews, and I use mutual influence variables instead of simple variables such as FDI–human capital and R&D–human capital interaction variables. Second, I examine how the FDI–human capital and R&D–human capital interactions are publicized in China's development process. I do so because, if words are simultaneously publicized, they should be considered as influence factors based on their correlations and interactions rather than as single influence factors. For this investigation, I conduct text mining analysis and degree centrality analysis using "FDI" and "R&D" as keywords. Third, on the methodological level, I employ two steps: the semantic network analysis (SNA) and vector error correction model (VECM) approaches. The former explores the possibility of interrelationships among three factors (FDI, R&D, and human capital) affecting China's economic development. I choose this method because it is predictable that the interactions of the variables can occur together on the basis of the network and clusters among the three factors. The latter is an empirical, analytical process that confirms whether the three mentioned factors can independently interact to form a causal relationship in the long or short run. The combination of the two methodologies not only improves the robustness of the research analysis and empirical models but also provides thoughtful insights to explain the effects between independent and dependent variables.

The paper is structured as follows. The following section theoretically explains the impact of FDI–R&D–human capital linkages on China's economic growth based on previous research. Section 3 sets up the two-step approach model—SNA and VECM. Data, methodology, and analysis results are presented for each step. Section 4 discusses the two-step analysis results along with policy implications. The conclusion and limitations are given in Section 5.

2. Literature Review

The theory of endogenous growth was developed by Romer [22] and Lucas [23]. It seeks to find factors that cause sustained economic growth in empirical models. R&D investment, global trade, and human capital are factors that make sustainable growth possible; they emphasize the spillover effect and learning through knowledge. In particular, FDI in developing countries stimulates a number of growth factors as driving forces for economic development. Therefore, under endogenous growth theory, FDI is an essential potential component of economic growth that increases the marginal productivity of the capital stock of host countries. However, the utilization of FDI's potential requires an economic environment of active FDI inducement policy in these countries (in this respect, the utilization of human capital and increased investment in infrastructure are important incentives to attract FDI). Economic growth may be adversely affected if such an economic environment is not established. In this case, the private investment rate by foreign capital can be increased, but it may not have a major influence on the increase in the social returns of host countries. This result follows because, in a distorted economic environment, the mere transfer of human capital and technology through FDI is not sufficient to raise the economic levels of such countries. Therefore, FDI, especially in developing countries, can interact with the human capital of host countries and, thus, affect economic growth.

A number of empirical studies investigate the effects of FDI on economic growth. These studies can be divided into those that argue for positive [10,24–27] and negative [28–33] effects. In particular, studies that claim negative effects explain that FDI induces a crowd-out effect, because it hinders the development of local economies [29]. From a balanced standpoint, the positive effect is said to exist only if a host country sets an appropriate regulatory policy on FDI and experiences political, economic, and social stability. Furthermore, some studies do consider FDI and human capital together. For example, Borensztein et al. [10] analyzed the effects of FDI and interaction (FDI*Schooling) variables on economic growth through a regression model. They proved that the interaction variables had significant positive results. A panel analysis of developing countries by Lipsey [34] showed that the interaction effect between FDI and education level in the previous period (t-1) had a crucial impact on economic growth. Zhang [35], in a study of eleven developing countries in East Asia and South America, demonstrated that FDI, trade liberalization, export orientation, and human capital have important effects on economic growth. Durham [36] reported that FDI differs depending on the absorption capacity of a host country. He argued that education and openness in developed countries led to greater FDI benefits. Similarly, Li and Liu [37] found that FDI had a positive impact on both developed and developing countries and that, in developing countries, human capital and FDI interacted with each other and had a significant positive influence on economic growth.

Regarding research on the relationship between R&D and national development, there is no question that innovation through R&D drives economic growth and enhances national competitiveness. According to the theory of economic growth, growth that depends only on the inputs of production factors, such as labor and capital, is limited; hence, innovation through R&D is essential for sustainability. Therefore, many countries around the world have been actively expanding their R&D investments in order to achieve sustainable growth and raise people's standards of living. In particular, R&D's importance has further intensified with the debate on the fourth industrial revolution.

R&D promotes the growth of knowledge capital, such as research papers and patents. Knowledge capital, in turn, influences the entire national economy through imitation and diffusion. Importantly, in this context, R&D interacts with human capital and generates new knowledge based on existing accumulated knowledge—economic growth is based on this knowledge. However, the existing literature on the nexus of R&D and national development has mostly analyzed the contribution of R&D investment to economic growth through its effect on productivity [38–43]. In other words, these studies have shown that R&D investment contributes to economic growth by enhancing the productivity of industry and the whole country, increasing capital, which, in turn, affects economic growth.

Lichtenberg [42] suggested that private R&D investment has a positive effect on the level and growth rate of labor productivity—that the elasticity of private R&D stock to GNP is about one third of physical capital; that is, approximately 7%. Goel and Ram [39] analyzed the effects of R&D investment and intensity on the economic growth of 18 developed and 34 developing countries according to World Bank standards. The results show that, although R&D has a statistically positive impact, its significance is not high. Furthermore, Coe and Helpman [38] analyzed the relationship between domestic and foreign R&D investment and total factor productivity in 22 OECD countries. They found that the seven major developed countries (G7) have higher productivity gains, elasticity, and accumulation of R&D capital. In particular, a greater pursuit of open international trade has resulted in a greater positive impact of foreign R&D on domestic productivity. Guellec and Potterie [41] also measured the elasticity of R&D investment for OECD countries. The results showed that government R&D investment reveals a positive (+) value for productivity improvement. Estrada and Montero [44] analyzed the effects of R&D investment on long-term economic growth in seven countries (USA, Germany, Japan, UK, France, Italy, and Spain) from 1970 to 2006. In this study, although R&D investment had a positive effect on economic growth, government R&D sparked crowd-out effects and weakened private R&D investment.

However, rapid economic growth requires absorptive capacity and human capital to incorporate advanced technologies. Howitt and Mayer-Faulkers [45] and Dowrick and Rogers [46] emphasized the importance of human capital and technical education. Guellec and Potterie [41] found that active domestic R&D activities led to the diffusion of knowledge in human capital and the effective transfer of technology through it. In a relatively recent study, human capital variables have added to the understanding of the impact of R&D on growth. Bronzini and Piselli [47] empirically analyzed the long run equilibrium relationship between productivity, human capital, and R&D in Italy. They showed that regional infrastructure investment and R&D activities have positive effects on the productivity of a region. In particular, they explained that human capital has the greatest influence on a region's productivity improvement. Teixeira and Fortuna [48] reported the effect of efforts to emulate various advanced countries (human capital investment, R&D investment, and trade activities) on Portugal's long-term growth. The results showed that human capital, R&D activities, and trade all had positive impacts on long-term growth and particularly emphasized the importance of human capital investment over R&D investment. Bengoa et al. [49] assessed the TFP–R&D–human capital–social capital nexus across Spain for the period from 1980 to 2007. A panel cointegration analysis showed that public R&D had a positive impact on growth, whereas no statistically significant effect was found for private R&D. In addition, both human capital and social capital had significant impacts on TFP in the long run. Lopez-Rodriguez and Martinez-Lopez [50] tested hypotheses in 25 European countries, emphasizing that non-R&D activities (human capital, innovation intensity), as well as R&D innovation activities, are important factors for growth. The results showed that not just R&D activities but also non-R&D activities (especially human capital) served as major drivers of positive impacts on TFP. The brief results of literature reviews in this study are summarized in Table 1.

In sum, the impacts of FDI and R&D on economic growth can themselves explain economic growth. However, given the increasing importance of knowledge capital, FDI and R&D should be taken into account with human capital variables. Furthermore, the interactions between variables should also be analyzed to identify their impacts on economic growth.

Table 1. A summary of studies that explore how FDI/R&D inflows affect economic growth.

Study	Sample	Methodology	Variables		Major Findings
			Dependent Variable	Major Independent Variables	
Borensztein [10]	69 countries (1970–1989)	SLS (Panel)	E (Economic growth)	FDI, HC (Human capital)	FDI*HC → E (+)
Beugelsdijk and Zwinkels [24]	44 countries (1983–2003)	GMM (Panel)	E	HFDI (horizontal FDI), VFDI (vertical FDI)	HFDI → E (+); VFDI → E (+) in developed countries
Baharumshah and Thanoon [25]	8 East Asian countries (1982–2001)	DGLS (Panel)	E	FDI, SAV (gross domestic saving), LD (long-term debt)	FDI → E (+); SAV → E (+); LD → E(+)
Bwalya [26]	Zambia (1993–1995)	GMM (Panel)	E (Local firms)	HFDI, VFDI, RFDI (regional FDI)	HFDI → E (−); VFDI → E(+); RFDI → E (+)
Javorcik [27]	CEEC 10 countries (1993–2000)	OLS (Panel)	E	HFDI, VFDI	VFDI → E (+)
Agosin and Machado [28]	3 region (1970–1996)	FEM (Panel)	I (Investment-GDP ratio)	FDI	FDI → I (+) in Asia; FDI → I (+) in Africa; FDI → I (−) in Latin America
Fry [29]	16 developing countries (1966–1988)	OLS (Panel)	E	FDI, SAV	FDI → SAV (−); FDI → E (−)
De Mello [30]	33 countries (1980–1994)	VAR (Time series)FEM (Panel)	E	FDI	FDI → E (+) in 16 countries from OECD;FDI → E (−) in 17 countries from non-OECD
Mencinger [31]	8 transition countries (1994–2001)	Granger causality test (Panel)	E	FDI	FDI → E (−)
Zhang [35]	11 countries in East Asia and Latin America (1960–1997)	ECM (Panel)	E	FDI	FDI → E (+) in Singapore, Mexico, Hong Kong, Indonesia, and Taiwan
Ashraf et al. [32]	123 countries (2003–2011)	GMM (Panel)	TFP (total factor productivity)	FDI	FDI has no statistically significant effect on TFP
Durham [36]	80 countries (1979–1998)	OLS (Panel)	E (GDP)	FDI, EUD (education), O (trade openness)	FDI*O → E (+); EUD → E (+) in developed countries
Li and Liu [37]	84 countries (1970–1999)	SLS (Panel)	E	FDI, HC	FDI → E (+); FDI*HC → E (+) in developing countries
Coe and Helpman [38]	22 countries (1971–1990)	OLS (Panel)	TFP	DR&D (domestic R&D), FR&D (foreign R&D)	FR&D → TFP (+)
Griffith et al. [40]	12 countries (1971–1990)	ECM (Panel)	TFP	R&D, HC)	R&D → TFP (+); HC → TFP (+)
Guellec and Potterie [41]	16 OECD countries (1980–1998)	ECM (Panel)	MFP (multi-factorproductivity)	R&D (included type of business, foreign, public, government, and university)	R&D → MFP (+)
Lichtenberg [42]	74 countries (1964–1989)	NLSM (Panel)	LP (labor productivity)	R&D (private funded)	R&D → LP (+)
Lichtenberg and Potterie [43]	22 countries (1971–1990)	OLS (Panel)	TFP	FR&D, O	FR&D → TFP (+); O → TFP (+)
Estrada and Montero [44]	7 countries (1970–2006)	SVAR (Panel)	E (GDP)	R&D (included government and private)	R&D → E (+)
Dowrick and Rogers [46]	57 countries (1965–1990)	OLS, GMM(Panel)	E (heterogeneous growth)	R&D, EDU (education)	R&D → E (+); EDU → E(+)

Table 1. *Cont.*

Study	Sample	Methodology	Variables		Major Findings
			Dependent Variable	Major Independent Variables	
Bronzini and Piselli [47]	19 region in Italy (1980-2001)	FLMOS (Panel)	TFP	R&D, HC, ISI (infra structure investment)	R&D → TFP (+); HC → TFP (+); ISI → TFP (+)
Teixeira and Fortuna [48]	Portugal (1960–2001)	VAR (Time series)	TFP	R&D, HC, T (trade)	R&D → TFP (+); HC → TFP (+); T → TFP (+)
Bengoa et al. [49]	17 region in Spanish (1980–2007)	DOLS (Panel)	TFP	R&D (public, private), P (patents), HC	R&D (public) → TFP (+); P → TRP (+); HC → TFP (+)
Lopez-Rodriguez and Martinez-Lopez [50]	25 countries in EU (2004–2008)	OLS (Panel)	TFP	R&D, Non R&D (HC)	R&D → TFP (+); HC → TFP (+)

Notes: SLS = stage least squares, GMM = generalized method of moments, DGLS = dynamic generalized least squares, CEECs = central and eastern European countries, OLS = ordinary least squares, FEM = fixed effect model, VAR = vector autoregression, ECM = error correction model, NLSM = nonlinear least squares method, SVAR = structural vector autoregressive, FMOLS = fully modified ordinary least squares, E = economic growth (or GDP), I = investment GDP ratio, TFP = total factor productivity, MFP = multi-factor productivity, LP = labor productivity, FDI = foreign direct investment, HC = human capital, HFDI = horizontal FDI, VFDI = vertical FDI, SAV = gross domestic saving, LD = long-term debt, RFDI = regional FDI, EDU = education, O = trade openness, DR&D = domestic R&D, FR&D = foreign R&D, ISI = infra structure investment, T = trade, P = patents, respectively.

3. Materials and Methods

This study defines the role of FDI and R&D interaction with human capital in China's economic growth through the combination of two analysis methodologies: SNA and VECM. I focus on enhancing the robustness of the research model and interpreting it from abundant and diverse perspectives by pre-verifying the interrelationships among the variables through SNA before performing empirical analysis using the VECM. In other words, by analyzing unstructured data through SNA, I examine the mutual influence, centrality, and structural similarity of the words implied by the variables. Then, I verify the interactions and roles of the variables through the final analysis of the formal data using the VECM.

3.1. Step One: Semantic Network Analysis

SNA is a method for analyzing big data by finding patterns that are interconnected in the nonlinear relationship of unstructured data. Specifically, the SNA method treats the words collected through the main keyword as nodes in the network, and the connection relations and patterns between the words are regarded as semantic social relations [51]. By interpreting the structural features, I can explore the contexts in which a given keyword is discussed and understood in public and expert discourses [52]. In this regard, network theorists have argued that clusters or patterns derived from the frequency, co-occurrence, and centrality of words occurring in a network can explore the meanings represented in the text [53,54]. This study uses word frequency to construct the text mining, as well as term frequency-inverse document frequency (TF-IDF) and degree centrality analysis. SNA is established based on a matrix after word cleaning and text mining.

3.1.1. Data

Through ICTCLAS [55], using the keywords of FDI and R&D, this study gathered data for news and documents for a five-year period up to 2016 on a Chinese portal (Baidu, Beijing, China). Baidu, the leading Chinese search engine, accounts for more than 95% of the search market, making it the most appropriate channel for exploring China's discourse. In total, I picked up 5683 words (2326 for FDI and 3357 for R&D) from Baidu that were then analyzed after data cleaning. For SNA, about 80 top words were extracted for each keyword based on the occurrence frequency and degree centrality values.

3.1.2. Text Mining: TF-IDF and Degree Centrality

This study estimates TF-IDF and degree centrality using a Python module for Chinese words. These classifications are determined by importance based on the term frequency and centrality estimation, which is based on the focus of the links between nodes (words or texts) in the semantic network [56]. In this network, a node in a geodesic path between other pairs of nodes is considered to occupy a critical location.

The TF-IDF value is useful for extracting valuable information in the process of text mining with unstructured data. This value is a measure of the importance of a particular word in a document using statistical techniques. In other words, if the frequency of a certain word is high, it can be considered important in the document, but, conversely, it can also imply that the word is a universal word. Thus, the importance of a particular word increases in proportion to the frequency of its occurrence in the document, but, in fact, the importance must be offset by the frequency of the corpus word. TF-IDF values are used by search engines to extract the information that is most relevant to user queries, and they are a key criterion for associating and ranking documents [57]. Depending on the attributes of the connection relationship, centrality can be interpreted in various ways (e.g., degree, closeness, and betweenness) [58]. Degree centricity refers to the degree of strong connection and attention in the network, which can be useful as the simplest and most effective indicator of the power relationship across nodes [59,60]. Degree centrality is measured to the extent to which a node is connected to another node in the network. Table 2 shows the results of text mining for the two main subject words (FDI and R&D).

Table 2. The result of textmining on FDI/R&D.

		Human Capital-Related Words (TF-IDF/Degree Centrality)
Subject words	FDI	Entrepreneur (358.905/0.037), Coll. and Univ. (331.324/0.075), Talented Person (208.732/0.028), Human Resource (165.101/0.041), Research Paper (148.161/0.025), Knowledge (112.765/0.015), Investor (111.089/0.016), College Students (96.755/0.016), Junior College (91.589/0.011), Income (82.746/0.010), Salary (76.482/0.010), Doctor (73.396/0.010), Graduate Students (65.545/0.006), Works (63.293/0.006), Bonus (56.803/0.006)
	R&D	Research Paper (301.616/0.051), University (228.511/0.040), Academic Degree (199.626/0.013), Professional (193.823/0.019), Intelligence (187.768/0.019), Engineer (186.855/0.028), Master (184.159/0.010), Teaching (165.952/0.011), Curriculum (160.803/0.012), Talented Person (147.661/0.017), Wisdom Knowledge (140.015/0.002), Expert (116.755/0.008), Human Resource (109.888/0.013), Knowledge (109.741/0.012), Teacher (90.704/0.015), Academic (87.036/0.008)

Table 2 shows the results of textmining on FDI and R&D. Specifically, the table shows which words are selected based on more than 70 words with high frequency and importance among the 5638 words that were searched, extracted, and refined for FDI and R&D. First, in terms of the frequency and importance of terms related to FDI, words related to human capital (e.g., *Entrepreneur*, *Coll. And Univ.*, *Talented Person*, *Human Resource*, *Research Paper*, *Knowledge*, *Investor*, *College Student*, *Junior College*, *Income*, *Salary*, *Doctor*, *Graduate Student*, *Works*, and *Bonus*) are found. This relation implies that talented people are needed for local affairs in the process of FDI inflow, or that talented people are needed to utilize FDI after its inflow. In particular, from the centrality of the words related to FDI, *Coll. and Univ.* (TF-IDF/degree centrality ranking; 11/5), *Human Resource* (31/13), *Investor* (50/39), and *College Student* (52/38) are found to be low in frequency but highly centralized (see Appendix A Table A1). These results show that human resources, such as *investors* and *college students*, play an important role in the inflow and utilization of FDI, and that the intrinsic performance of FDI can be achieved through interactions with human resources beyond the inflow of FDI.

Second, a total of 3357 related words are collected using R&D as the main word. The top 82 words are extracted based on frequency, importance, and centrality. As with the results of the FDI-related word analysis, words associated with human capital (e.g., *Research Paper*, *University*, *Academic Degree*, *Professional*, *Intelligence*, *Engineer*, *Master*, *Teaching*, *Curriculum*, *Talented Person*, *Wisdom Knowledge*, *Expert*, *College*, *Human Resource*, *Knowledge*, *Teacher*, and *Academic*) are also relatively high among the R&D-related words. This result means that R&D cannot be considered separately from human capital. The basic premise of R&D goes hand in hand with the intellectual output of academics and experts. Therefore, quantitative growth, such as R&D investment, is important, but qualitative growth that utilizes human resources appropriately is also an important factor for deriving R&D results. The notable words are *University* (TF-IDF/degree centrality ranking; 20/9), *Engineer* (31/15), *Talented People* (44/36), *College* (61/38), *Human Resource* (64/50), *Knowledge* (65/55), and *Teacher* (79/44). These words appear to have relatively high centralities but low frequencies of occurrence (see Appendix A Table A2). This result implies that human capital has a positive influence on R&D. Furthermore, the availability of competent human resources is directly related to R&D performance.

In sum, I have confirmed that human resources are closely related to FDI and R&D. This finding raises the need to look at the interaction effects, as well as the independent effects between the three factors, and it also serves as a basis for enhancing the robustness of the interaction variables (FDIHC, RDHHC) used in this analysis. In particular, in terms of absorptive capacity, the results of text mining support the finding that an influx of FDI brings more benefits to developed countries where human capital is relatively developed [36,37], and that R&D investment in human capital should precede infrastructure investment [47].

3.1.3. Results of SNA

Convergence of iterated correlations (CONCOR) analysis, a type of semantic network analysis, is applied in this study. First, based on extracted unstructured data related to the main subjects (FDI and R&D), I construct a co-occurrence matrix of words x words using WORDij. WORDij (http://wordij.net) is a program used to analyze various types of unstructured data, as in computational linguistics, text, and content analysis, and network visualization [52]. Second, I use the CONCOR matrix (correlation or eigenvalue) to determine the similarities and patterns of relationships between the row vectors of each node [51,61]. The CONCOR analysis is performed to identify semantic clustering in the entire network surrounding the topic, to discover hidden subgroups, and to explore the relationships between the groups [62,63]. In this study, SNA is performed based on the correlation matrix between words. In particular, I perform CONCOR analysis to cluster words and identify the nature and properties of major clusters; the results of this analysis are shown in Table 3.

Table 3. The result of the CONCOR analysis.

	Subject Word	
	FDI	R&D
Number of clusters	5	4
Average clustering coefficient	5.157	2.263
Major hub nodes	FDI, Dollar, Shandong, Entrepreneur, Branch Office, Global, Coll. and Univ., Talented Person	System, Technology, Project, Enterprise, New Drug, Research Paper, Academic Degree, Master
Significant keywords in the cluster (human capital perspective)	Entrepreneur, Coll. and Univ. A Talented Person, Human Resource, Research Paper	Research Paper, University, Academic Degree, Engineer, Master, Teaching, Talented Person, Wisdom Knowledge, Expert, Human Resource, Knowledge

A total of five clusters are found in SNA related to FDI. The average clustering coefficient is 5.157, which implies tightness with neighboring nodes. There are eight major hub nodes, and three hubs are associated with human capital (*Entrepreneur*, *Coll. and Univ.*, and *Talented Person*). Furthermore, I identify two significant keywords (*Human Resource* and *Research Paper*) related to human capital in addition to the hub node in the cluster. For R&D, four clusters are identified, and the average coefficient is 2.263. There are nine main hubs in the network and three hubs (*Research Paper*, *Academic Degree*, and *Master*) related to human capital. Additionally, it can be seen that 11 keywords among the words in the cluster are relatively strongly related to human capital.

Specifically, I find that words related to advanced talent (e.g., *Talented Person*, *Knowledge*, and *Human Resource*) play an important role in various fields where FDI is used (e.g., *Finance*, *One Road One Belt*, *Fund Management*, and *Project Management*). In other words, the results show that the role of human capital is necessary to enhance the effectiveness of FDI, which can aid host countries when various human capital factors interact with FDI (see Appendix B, Figure A1).Regarding R&D, the main clusters contain words referring to R&D core fields, such as *Information*, *Software*, *Computer*, *Technology*, and *Machine*, and words related to human capital (e.g., *Professional*, *Expert*, *Academic Degree*, and *Master*), which are bound together. In other clusters, companies are interested in utilizing human capital in production and strategic management processes through R&D activities. Furthermore, they have been attempting to maximize R&D performance through the interaction between R&D and human capital. The results suggest that R&D must be supported by human capital (*researchers*, *experts*, etc.) in order to have a positive impact on the economic growth of a host country. In addition, the SNA result that examines the contribution of economic growth to R&D and human capital interactions is more meaningful than that of simple R&D investment to economic growth (see Appendix B, Figure A2).

3.2. Step Two: VECM Analysis

The advantage of a multivariable equation is that the disturbance of a particular variable can be corrected by a single variable or a combination of variables. The cointegrating vector error correction (VEC) equation is also a spin-off framework with the ability to coordinate and respond to disturbances when a different set of variables is observed within the variables [64]. Hence, based on the VECM, this study examines the relationship between interaction variables (FDI-and R&D-human capital) and China's economic growth. In particular, I set up a comparative model consisting of FDI, R&D, and GDP to examine the relative elasticities of the interaction variables.

3.2.1. Data

The data used for the verification of this study model were collected using an online data set provided by the National Bureau of Statistics of China (http://data.stats.gov.cn) based on the China Statistical Yearbook, the China Labor Yearbook, the China R&D Yearbook, and the Statistics Department of the Commerce Department of China. The data in this analysis use a time series from 1991 to 2016, wherein FDI- and R&D-related statistics coexist. FDIHC is the interaction variable between FDI and human capital. The FDI value (FDI) indicates the total amount of foreign investment actually incurred by firms each year, and human capital (HC) represents the growth rate of new employees among college graduates each year. R&D-human capital is the interaction variable between R&D and human capital. The R&D value (RD) refers to the total amount invested in R&D each year, and human capital (HHC) refers to the annual growth rate of regular workers in R&D-related industries. All variables are converted into real values based on1991 prices and substituted into the model after taking natural logs.

3.2.2. Methodology

According to the Monte Carlo evidence reported by Guilkey and Salemi [65] and Geweke et al. [66], among many techniques, Granger causality tests provide the most reliable results for small sample sizes. Thus, Granger causality tests [67] based on the VAR model are applied in this study to analyze the nexus between FDI-human capital interaction, R&D-human capital interaction, and economic growth. These tests, however, must fit the assumption that the time series variables used in the model are stable. If the time series variables are non-stationary, the data stability condition for applying the VAR model is violated, resulting in an invalid Granger causality test statistic. Granger [67] pointed out that if variables are non-stationary and cointegration exists after the first difference, then the model that is suitable for investigating the relationship between these time series variables is the VECM. Applying the main variables used in this study, the equation is expressed as follows:

$$\Delta GDP_t = c_1 + \sum_{i=1}^{n} \alpha_{1i} \Delta GDP_{t-i} + \sum_{j=1}^{n} \beta_{1j} \Delta FDIHC_{t-j} + \sum_{k=1}^{n} \gamma_{1k} \Delta RDHHC_{t-k} + \varnothing_1 ETC_{t-1} + \epsilon_{1t} \quad (1)$$

$$\Delta FDIHC_t = c_2 + \sum_{i=1}^{n} \alpha_{2i} \Delta FDIHC_{t-i} + \sum_{j=1}^{n} \beta_{2j} \Delta RDHHC_{t-j} + \sum_{k=1}^{n} \gamma_{2k} \Delta GDP_{t-k} + \varnothing_2 ETC_{t-1} + \epsilon_{2t}$$

$$\Delta RDHHC_t = c_3 + \sum_{i=1}^{n} \alpha_{2i} \Delta RDHHC_{t-i} + \sum_{j=1}^{n} \beta_{3j} \Delta GDP_{t-j} + \sum_{k=1}^{n} \gamma_{3k} \Delta FDIHC_{t-k} + \varnothing_3 ETC_{t-1} + \epsilon_{3t}$$

in which $\mathbf{c}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ are coefficients of the polynomial; n is the optimal lag; $\boldsymbol{ETC_{t-1}}$ is the correction term; and $\boldsymbol{\epsilon_{1t}}$ is the disturbance term. Equation (1) expresses the causality test model from ***FDIHC*** and ***RDHHC*** to ***GDP***. If the null hypothesis ($\boldsymbol{H_0 : \beta_{1j} = \gamma_{1k} = 0}$) is rejected in Equation (1), short-run Granger causality is established from ***FDIHC*** and ***RDHHC*** to ***GDP***. The coefficient ($\boldsymbol{\varnothing_1}$) of the error correction term shows the speed of adjustment towards equilibrium. As such, if the null hypothesis ($\boldsymbol{H_0} : \varnothing_1 = \mathbf{0}$) is rejected, long run Granger causality is established from right to left. Similarly, in the causality test model from ***RDHHC*** and ***GDP*** (or ***GDP and FDIHC***) to ***FDIHC*** (or ***RDHHC***), rejection of the null hypotheses $\boldsymbol{H_0} : \boldsymbol{\beta_{2j}} = \boldsymbol{\gamma_{2k}} = \mathbf{0}$ and $\boldsymbol{H_0} : \varnothing_2 = \mathbf{0}$ (or $\boldsymbol{H_0} : \boldsymbol{\beta_{3j}} = \boldsymbol{\gamma_{3k}} = \mathbf{0}$ and $\boldsymbol{H_0} : \varnothing_3 = \mathbf{0}$) reflects short run Granger causality from right to left.

3.2.3. Unit Root Test

If the stationarity of the time series variables is not secured, a spurious regression phenomenon, which appears to be irrelevant to the regression analysis, can be found. Therefore, a unit root test is performed to determine the stability of the time series data. Key techniques of the unit root test are the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The ADF test is most widely used, as it accounts for possible serial correlation term by adding lagged dependent variables but assumes that the correction terms are free of heteroscedasticity [68]. The PP test [69] makes a non-parametric correction for serial correlation while taking into consideration both autocorrelation and heteroscedasticity. The optimal lag length is selected based on the Schwartz information criterion [70]; all kinds of cases, such as "constant," "constant with trend," and "none", are considered.

Table 4 shows the results of the ADF and PP unit root tests for the FDI, RD, HC, HHC, FDIHC, RDHHC, and GDP time series data. The results indicate that the null hypothesis (unit root exists) is not rejected at the 1% significance level, which means that the time series variable is not stable when it is a level variable. Therefore, in order to apply the variable correctly to the model, it is suggested to use strictly standard data with a higher-level variable, namely, a differential variable. However, the null hypothesis that the seven time series data are unstable is rejected at the 1% significance level after first differencing. All variables introduced in the model can be categorized as non-stationary time series data, but the first difference variables are found to be stable time series data with no unit roots.

Table 4. Results of the unit root tests.

Variables		ADF			PP		
		C	**CT**	**None**	**C**	**CT**	**None**
GDP	Level	−1.991	−2.761	0.929	−0.743	−2.695	0.282
	Δ	−6.121 ***	−5.958 ***	−5.739 ***	−9.229 ***	−8.947 ***	−5.500 ***
FDI	Level	−0.598	−1.713	2.975	−0.598	−1.789	2.777
	Δ	−4.601 ***	−4.494 ***	−3.168 ***	−4.597 ***	−4.489 ***	−3.077 ***
RD	Level	−0.320	−2.727	1.047	−0.481	−2.010	0.683
	Δ	−3.532 ***	−3.865 ***	−3.188 ***	−3.518	−3.444 **	−3.235 ***
HC	Level	−2.031	−1.952	−1.002	−1.898	−1.820	−1.422
	Δ	−4.542 ***	−4.616 ***	−4.654 ***	−3.741 ***	−4.546 ***	−3.877 ***
HHC	Level	−3.011 **	0.008	−0.954	−2.896 *	−2.944	−1.427
	Δ	−8.347 ***	−8.494 ***	−8.534 ***	−8.956 ***	−13.392 ***	−9.189 ***
FDIHC	Level	−0.320	−3.340 *	0.659	−1.355	−3.317 *	−0.592
	Δ	−9.005 ***	−3.712 ***	−8.677 ***	−9.592 ***	−9.575 ***	−8.820 ***
RDHHC	Level	−3.959 ***	−4.175 **	−3.710 ***	−1.474	−1.340	−1.070
	Δ	−4.058 ***	−4.131 **	−4.147 ***	−4.117 ***	−4.185 ***	−4.201 ***

Note: ADF stands for augmented Dickey-Fuller test; PP stands for Phillips Perron test; C stands for constant; CT stands for constant and trend; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.2.4. Cointegration Test

Since the unit roots are found to exist in each time series, I next determine the cointegration relation of the variables. The Johansen test, regarded as the most superior cointegration test, enables various types of hypothesis testing in addition to estimating the cointegration parameter. Thus, I use the Johansen [71] test to determine the cointegration of time series variables used in the model. As in the unit root test, to reduce bias and ensure accurate results, optimal lags are selected to minimize the Schwartz [70] criterion statistics.

The results of the cointegration test using the Johansen test method are shown in Table 5; both trace and maximal eigenvalue tests are applied. Both test results are able to reject the null hypothesis that no cointegration exists at the 1% significance level. The null hypothesis (H_0: r $\leq$ 1) that a maximum of one cointegration exists cannot be rejected, which indicates that one cointegration exists. Thus, there exists a long run balanced relationship between the variables of model 1 and model 2.

Table 5. Results of the Johansen cointegration test.

Models	Null Hypothesis	Trace Statistics	5% Critical Value	Prob.	Max Eigenvalue	5% Critical Value	Prob.
Model 1	H0: r = 0	33.141 **	29.797	0.020	23.236 **	21.132	0.025
	H0: r $\leq$ 1	9.906	15.495	0.288	9.903	14.265	0.218
	H0: r $\leq$ 2	0.003	3.841	0.955	0.003	3.841	0.955
Model 2	H0: r = 0	47.994 **	29.797	0.000	38.964 **	21.132	0.000
	H0: r $\leq$ 1	9.030	15.495	0.363	8.255	14.265	0.353
	H0: r $\leq$ 2	0.775	3.841	0.379	0.775	3.841	0.379

Note: Model 1: The cointegration between GDP, FDI, and RD; Model 2: The cointegration between GDP, FDIHC, and RDHHC; r denotes the number of cointegrating vectors; optimal lag = 3 based on SC statistics; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.2.5. Causality Analysis Using a VECM

In the preceding test, I find that each time series variable has a unit root and that a cointegration vector exists between the variables of model 1 and model 2.Hence, I conduct Granger causality tests [67] based on the VECM. The VECM assumes that all variables included in the model are regarded as endogenous. In order to test causality using the VECM, the appropriate time lag should be selected for the model. Since the time lag structure has a sensitive effect on the result of the causality test, if the number of time lags is arbitrarily set, it can distort the estimation factor and lead to false causal reasoning. This study uses a model with a time lag of three at the minimum SC statistic. I conduct the Granger causality test by estimating the following VECM:

$$\begin{bmatrix} \Delta GDP_t \\ \Delta FDIHC_t \\ \Delta RDHHC_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \sum_{i=1}^{n} \begin{bmatrix} \theta_{11i} & \theta_{12i} & \theta_{13i} \\ \theta_{21i} & \theta_{22i} & \theta_{23i} \\ \theta_{31i} & \theta_{32i} & \theta_{33i} \end{bmatrix} \begin{bmatrix} \Delta GDP_{t-i} \\ \Delta FDIHC_{t-i} \\ \Delta RDHHC_{t-i} \end{bmatrix} + \begin{bmatrix} \varnothing_1 \\ \varnothing_2 \\ \varnothing_3 \end{bmatrix} [ECT_{t-1}] + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix} \quad (2)$$

in which Δ represents the first difference operator. $\boldsymbol{c_i}$s and $\boldsymbol{\epsilon_{it}}$s represent intercepts and error terms of each equation for $\boldsymbol{i = 1, 2, 3}$, respectively. $\boldsymbol{ECT_{t-1}}$ indicates the error correction term (in model 1, Δ***FDI*** and Δ***RD*** values are substituted for Δ***FDIHC*** and Δ***RDHHC***, respectively). In the long run, if the coefficients on the error correction terms are statistically significant using *t*-statistics, then there is a causal link from the independent variable to the dependent variable. In order to determine whether short run causality exists, the joint significance of the coefficients of each independent variable should be tested using the *F*-statistics of the Wald test. If the *F*-statistic of the explanatory variable is significant, then there is a short run causal relationship between that variable and the dependent variable [72]. In this study, I use the Granger causality test based on VECM to investigate the causal relationship between long and short run variables. The results of the causality test are shown in Table 6.

Table 6. Results of the VECM Granger causality test.

Models	Dependent Variables	Type of Granger Causality						Inferences
		Short Run					Long Run	
		ΔGDP	ΔFDI	ΔRD	ΔFDIHC	ΔRDHHC	ETCt-1	
	ΔGDP		12.642 ***	5.427			0.678 ***	FDI≥GDP;RD≠>GDP
Model 1	ΔFDI	3.819		5.237			0.009	GDP≠>FDI;RD≠>FDI
	ΔRD	13.967 ***	25.808 ***				0.013 ***	GDP≥RD;FDI≥RD
	ΔGDP				15.190 ***	19.914 ***	−0.193 ***	FDIHC≥GDP;RDHHC≥GDP
Model 2	ΔFDIHC	65.001 ***				15.211 ***	24.520 **	GDP≥FDIHC;RDHHC≥FDIHC
	ΔRDHHC	10.887 **			39.629 ***		0.313 ***	GDP≥RDHHC;FDIHC≥RDHHC

Note: Model 1: The VECM between GDP, FDU, and R&D; Model 2: The VECM between GDP, FDIHC, and RDHHC; ≥ means that the left side can cause the right side; ≠> means that the left side cannot cause the right side; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

According to these results, first, the long run balance relation can be observed through whether the error correction term estimation coefficient (∅) of the previous period (t-1) has a negative sign. The results of this estimation show that the effects of FDIHC and RDHHC on GDP are all statistically significant (FDIHC→GDP; RDHHC→GDP), which implies that FDIHC and RDHHC have mutually long run effects on GDP. However, there is no long run impact of RDHHC and GDP on FDIHC or of FDIHC and GDP on RDHHC. Second, in the short run Granger causal analysis, it is only necessary to test whether the coefficient of each differenced explanatory variable is statistically significant. According to the results of this estimation (based on the Wald test), FDIHC and RDHHC affect GDP in the short run (FDIHC→GDP; RDHHC→GDP), and FDIHC and RDHHC are mutually affected in the short run (FDIHC↔RDHHC). In Model 1, there is no long run effect between GDP, FDI, and R&D; in the short run, FDI affects GDP, and GDP and FDI affect R&D (FDI↔GDP; FDI→R&D). Comparing Model 1 and Model 2 shows that FDI has a significant impact on GDP growth in the long run when interacted with human capital. This result suggests that a country's continuous development requires the input of human capital along with various development factors. This result also shows that an organic combination of human capital and a driving force for development, such as FDI or R&D, is important in the short run.

In addition, I conduct the variables decomposition test and present the result in Table 7. This result can bolster the Granger causality finding explained above. The variance decomposition of the prediction error is a methodology for measuring the relative importance of each variable in the model. First, in Model 1, GDP is explained by the impact of GDP in the short run, and, in the long run, the explanatory power of R&D increases to more than 20%. For FDI, the explanatory power increases to 12% in the long run, but in the medium term, the explanatory power decreases to 4%, which indicates a relatively dynamic change overall; in the short run, FDI has a self-explanatory power of 42%, but in the long run, its own driving force for growth falls to 3.8%. For R&D, the explanatory power of GDP and R&D gradually decline over time; the explanatory power of FDI relative to R&D gradually increases to 13%.Applying the variance decomposition method to model 2 establishes that almost 100% of GDP is explained by shocks to GDP in the short run. In the long run, FDIHC and RDHHC account for economic growth of 8% and 56%, respectively (see Table 6, model 2). Furthermore, FDIHC is hardly affected by other variables (GDP and RDHHC) in the short run. However, in the long run, the explanatory power of FDIHC is reduced to 34%, and the RDHHC has more than 50% explanatory power. Finally, RDHHC shows a self-explanatory power of 50% in both the short and long run. FDIHC shows strong explanatory power over time, but GDP shows weak explanatory power over time. Taken together, the human resources in the R&D sector have a significant impact on GDP, FDI, and R&D itself in the long run. This finding implies that R&D input requires investment in software, as well as hardware, and that there is a need for uncompromising investment in professional researchers and advanced talent.

Table 7. Results of the variance decomposition test.

Model 1	Period	Variance Decomposition of GDP:			Variance Decomposition of FDI:			Variance Decomposition of RD:		
		GDP	FDI	RD	GDP	FDI	RD	GDP	FDI	RD
	1	100.000	0.000	0.000	57.744	42.256	0.000	5.196	3.011	91.793
	2	87.815	11.426	0.758	73.113	23.863	3.023	53.172	1.406	45.422
	3	86.537	11.483	1.981	78.482	17.939	3.579	82.324	2.519	15.157
	4	86.436	5.584	7.981	77.944	12.140	9.916	92.215	1.413	6.372
	5	82.320	3.901	13.779	78.786	8.200	13.015	89.006	1.497	9.497
	6	75.875	5.446	18.678	76.722	6.498	16.780	82.146	2.409	15.445
	7	70.521	7.914	21.565	75.955	5.551	18.495	74.512	5.309	20.179
	8	67.682	9.978	22.340	76.522	4.701	18.777	68.985	8.804	22.210
	9	66.266	11.826	21.908	77.296	4.364	18.340	65.945	11.695	22.360
	10	66.649	12.225	21.126	78.568	3.886	17.545	65.453	13.196	21.351
Model 2	Period	Variance Decomposition of GDP:			Variance Decomposition of FDIHC:			Variance Decomposition of RDHHC:		
		GDP	FDI HC	RD HHC	GDP	FDI HC	RD HHC	GDP	FDI HC	RD HHC
	1	100.000	0.000	0.000	0.111	99.889	0.000	34.961	9.886	55.153
	2	92.431	0.085	7.484	0.666	93.845	5.489	46.818	15.786	37.396
	3	86.651	0.482	12.867	9.036	82.328	8.636	37.850	16.274	45.877
	4	73.417	0.585	25.998	8.375	79.250	12.375	31.800	19.019	49.181
	5	59.944	1.600	38.456	19.070	51.688	29.242	26.535	19.421	54.043
	6	54.724	2.382	42.894	23.455	37.442	39.102	29.518	15.838	54.644
	7	49.747	3.805	46.447	20.199	37.253	42.548	31.541	14.153	54.306
	8	42.652	5.810	51.538	16.087	38.751	45.162	28.512	16.374	55.114
	9	37.212	7.356	55.432	13.162	38.459	48.379	25.815	19.219	54.966
	10	35.352	7.983	56.666	14.171	34.651	51.179	23.886	21.135	54.979

4. Discussion

According to the development paths that many countries have followed, growth factors can be divided into material and human resource development, both of which impact sustainability. Material resources can be further divided into domestic and foreign capital, and human resources can be divided into simple labor and high-quality human capital. In general, in the early stage of national development, simple labor and foreign capital become the main driving force for development; however, domestic capital and high-quality human capital are important for the country to develop at a certain level and to continue to develop.

Since the Chinese economic reforms of 1978 (or "reform and opening-up"), the country has mobilized enormous human and material resources to lead development. Until 1990, labor-intensive industries, combined with foreign capital and cheap labor, led to a boom in the economy. After 1990, domestic and foreign capital in the market, along with simple and high-level labor forces, were used to further lead economic growth. Currently, China has been following a low growth trend with the New Normal. It has so far established a socialist market economic system, characterized by Chinese traits, in order to achieve a sustainable society.

In particular, industrial restructuring, the training of start-up talent, and global infrastructure projects have been driving forces for Chinese growth. However, a wide range of growth concerns has also arisen. Despite these concerns, the country has continued to find drivers for sustainable growth, pursuing economic growth in line with its methods. Hence, our interest lies in the human capital enhancement policy that China has pursued steadily since its "reform and opening-up." FDI and R&D can combine with high-quality human capital to maximize investment performance, which can be explained by the fact that China has been able to record GDP growth of close to 10% since the 1990s. In the future, its power to pursue stable and sustainable growth is "people"; hence, I analyze economic growth through the interaction between material resources (FDI and R&D) and human capital using a two-step approach (SNA and VECM).

This study has several implications. First, FDI and R&D, which have maintained growth in China, have formed many networks related to human capital. This finding, again, serves as a reminder to not overlook human capital factors in analyzing the impacts of FDI and R&D on economic growth in general. Particularly, in countries that are in the process of transition from state-led development to private-led development, such as China, the importance of human capital has been increasing [73].

This means that there is an increase in opportunities that could stimulate domestic education, an inflow of more high-quality human capital to the market, and the efficient utilization of labor resources. In particular, given the keywords of economic growth in China—namely, the transition to economic and sustainable development—the role of advanced talent in R&D becomes even more important. From the perspective of absorption capacity, our results support the notion that, no matter the quality of the FDI and R&D activities undertaken, if human capital has not been formed to accept them, then the two main factors for economic growth are limited [37]. Therefore, given the network analysis results, China should continue to pursue FDI and R&D input policies but must pursue efficiency and efficiency maximization strategies combined with human capital.

Second, according to the results of the VECM analysis, China's reforms after the 1990s have been relatively successful [74]. The technology and management know-how of multinational corporations in China have been sufficiently transferred, and human capital that can utilize them has been developing in line with FDI inflows. In particular, China, which is accustomed to accepting foreign culture, seems to have rapidly absorbed the cultures of foreign companies in order to generate sufficient synergy with domestic human capital and foreign companies. This process is desirable not only for emphasizing quantitative aspects in the process of attracting FDI but also for considering qualitative aspects, such as the transfer of advanced technology and advanced management techniques. In addition, cultivating qualitative talent through education at a global level, beyond the development of quantitative human resources, will enable the synergetic effects of human capital with foreign companies in China. In other words, there should be a qualitative improvement at the level of global education that can be easily applied and adapted to the culture and ability of the enterprise that foreign companies demand.

In terms of R&D, it is also necessary to give sufficient consideration (salary and welfare) to Chinese advanced manpower, which has been improving steadily. We must establish a policy to maximize the efficiency and effectiveness of R&D inputs. In particular, in order to obtain good results in terms of their attributes, R&D inputs should be promoted from mid- and long-term perspectives rather than from a short-term perspective. Currently, it is crucial to support high-level personnel who are patient and work within the R&D field. Nevertheless, China has a variety of policies created to attract talented overseas human resources and to cultivate high-quality human resources. However, considering the current economic situation, which is still highly likely to develop, it is necessary to foster more advanced human resources within China and to attract foreign talent to enhance the effectiveness of R&D investment utilization.

5. Conclusions

This study investigated the influence of the driving forces of the national economy—FDI and R&D—on GDP growth when interaction variables with human capital were also included. Based on the literature on endogenous economic development, this study identified FDI and R&D, which affect national development, as key variables; it then examined the effect of the interaction with human capital on GDP as a factor for sustained economic growth.

First, I looked at the extent to which human capital-related words are connected through data mining—with FDI and R&D as keywords—and identified the clusters of words related to FDI, R&D, and human capital through network analysis. This analysis confirmed that the roles and importance of human capital in FDI and R&D input are strongly connected. In other words, in studying the effects of FDI and R&D on sustainable economic development, I found that interaction variables combined with human capital should be applied over a single variable.

Second, based on the results of network analysis, VECM was implemented by interacting the FDI and R&D variables with human capital, and the results were compared to those of the model with the missing human capital factor (GDP-FDI-R&D). The FDI-human capital and R&D-human capital interactions showed positive (+) influences on GDP growth both in the short and long run. In particular, the R&D-human capital interaction was shown to have a significant impact on GDP growth compared to the FDI-human capital interaction. This finding leads us to conclude that it is necessary to nurture high-quality human resources for continuous national development and create an environment in which they can engage in work and achieve results. In addition, the FDI- and R&D-human capital interactions are mutually influential, which can be seen as a complementary relationship between FDI, R&D, and human capital, leading to national development.

Based on these results, academic implications can also be drawn. First, when discussing national development, it is necessary to consider human capital, as well as FDI and R&D, and, especially, the influence of the interaction between these variables on national growth. Second, in the study of national economic growth, the robustness of the variables used in the research model should be improved upon by using unstructured data. Attempts must be made to identify the various meanings of unstructured data and to find words and variables that could be meaningfully applied to future research. Third, it is important to continue to expand FDI and R&D in order to overcome low growth and improve sustainable economic growth. However, it is necessary to educate and attract talent to maximize the efficiency of the inputs. It is also necessary to invest capital in accordance with national characteristics and development goals in detail and, at the same time, to cultivate human resources to maximize investment performance.

Despite the aforementioned meaningful results, this study has certain limitations. First, I did not consider the spillover, dynamic, and crowding out effects among variables, because the statistical data available in each region in China are still very limited. Future research and policy implications can be derived if these data are systematically constructed. Second, I also did not consider the qualitative aspects of human capital in the process of selecting interaction variables. In addition to FDI, R&D, and human capital, there are factors that influence national development, but they are not considered comprehensive. This raises the need to consider interactions with new variables, such as ICT technological aspects, information and communication infrastructure, and national maturity, while taking into account the increasing complexity of development factors.

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Appendix A

The text mining technique used in this study utilizes the TF-IDF value, which measures the importance of words in a document, and the degree centrality value, which measures the connection centrality of words in the document. In using the TF-IDF value, this study applies a typical measurement formula (see Equation (A1)) [57]:

$$\mathrm{TF}-\mathrm{IDF} = \mathrm{TF} \times \mathrm{IDF} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right) \tag{A1}$$

in which $\boldsymbol{tf_{x,y}}$ denotes the frequency of $\boldsymbol{x}$ in $\boldsymbol{y}$, $\boldsymbol{df_x}$ denotes the number of documents containing $\boldsymbol{x}$, and $\boldsymbol{N}$ indicates the total number of documents.

In terms of degree centrality, for the non-directional/binary graph including g nodes, the degree centrality of node i is obtained by summing the number of connections that node i makes with the remaining $(n-1)$ other nodes (see Equation (A2)) [75]:

$$C_D(N_i) = \sum_{j=1}^{g} x_{ij},\ i \neq j \tag{A2}$$

in which $\boldsymbol{C_D(N_i)}$ denotes the degree centrality of node $\boldsymbol{i}$, $\boldsymbol{g}$ is the number of nodes, and $\sum_{\boldsymbol{j=1}}^{\boldsymbol{g}} \boldsymbol{x_{ij}}$ indicates the number of connections that node $\boldsymbol{i}$ has with the $(\boldsymbol{g-1})$ other nodes. Degree centrality according to Equation (A2) is influenced by the size of the network. Therefore, it is necessary to eliminate the influence of the network size on degree centrality in order to compare the nodes. Considering the network size, the standardized formula is as follows (see Equation (A3)):

$$C'_D(N_i) = \frac{C_D(N_i)}{g-1} \tag{A3}$$

in which $C'_D(N_i)$, $C_D(N_i)$, and g denote the standardized degree centrality of node i, the degree centrality of node i, and the number of nodes, respectively.

Table A1. The results of the relative term frequency and centrality for FDI.

Words	TF-IDF	Rank	Degree Centrality	Rank	Words	TF-IDF	Rank	Degree Centrality	Rank
FDI	542.714	1	0.246	1	Bank	142.879	38	0.015	42
China Gov.	536.496	2	0.128	2	Foreign Exchange	137.295	39	0.014	46
Korea	487.784	3	0.038	14	Countermeasure	129.427	40	0.015	40
Dollar	431.138	4	0.091	4	Journalism	128.555	41	0.025	24
Shandong	428.459	5	0.024	29	Scale	127.316	42	0.017	36
Economy	407.188	6	0.097	3	Service Industry	124.423	43	0.011	53
China	369.276	7	0.053	7	Zhejiang	122.326	44	0.008	66
Entrepreneur	358.905	8	0.037	16	Technology	119.355	45	0.012	48
Enterprise	338.949	9	0.061	6	Platform	118.146	46	0.008	62
Foreign Fund	335.059	10	0.051	9	One Road One Belt	116.597	47	0.014	45
Coll. And Univ.	331.324	11	0.075	5	System	115.138	48	0.016	37
Industry	330.805	12	0.035	19	Knowledge	112.765	49	0.015	43
Global	324.308	13	0.045	10	Investor	111.089	50	0.016	39
Hong Kong	317.320	14	0.037	15	Information	98.738	51	0.015	41
Trade	304.533	15	0.045	11	College Students	96.755	52	0.016	38
Foreign Company	304.184	16	0.052	8	Stock	96.608	53	0.008	61
Investigation and Research	279.048	17	0.035	18	Anhui	95.287	54	0.014	44
RMB	278.645	18	0.042	12	GDP	93.783	55	0.007	68
Project	230.845	19	0.034	20	Junior College	91.589	56	0.011	50
Ministry of Commerce	228.511	20	0.008	67	Region	82.863	57	0.011	51
Contract	212.697	21	0.011	52	Income	82.746	58	0.010	55
Talented Person	208.732	22	0.028	23	Fujian	81.102	59	0.008	65
Finance	206.111	23	0.032	22	India	78.602	60	0.012	47
Heilongjiang	205.364	24	0.011	50	Management	76.482	61	0.010	59
Market	189.564	25	0.033	21	Salary	76.482	62	0.010	58
Structure	188.569	26	0.020	33	Foreign Trade	75.436	63	0.008	64
Effect	182.001	27	0.025	27	Manufacturing Industry	74.281	64	0.010	54
USA	181.326	28	0.020	32	Doctor	73.396	65	0.010	56
Data	170.532	29	0.036	17	Guangzhou	73.396	66	0.006	70
Capital	169.421	30	0.023	29	Bonds	69.911	67	0.009	60
Human Resource	165.191	31	0.041	13	Competitiveness	66.908	68	0.006	72
Shanghai	161.706	32	0.018	34	Africa	65.896	69	0.008	63
Country	155.271	33	0.025	26	Graduate Students	65.542	70	0.006	69
Relationship	152.256	34	0.021	31	Beijing	65.241	71	0.006	71
Policy	150.206	35	0.018	35	Works	63.293	72	0.006	73
Research Paper	148.161	36	0.025	35	Science Technology	59.073	73	0.010	57
Finance and Economy	143.795	37	0.023	30	Bonus	56.803	74	0.006	74

Table A2. The results of the relative term frequency and centrality for R&D.

Words	TF-IDF	Rank	Degree Centrality	Rank	Words	TF-IDF	Rank	Degree Centrality	Rank
System	587.789	1	0.122	1	Contents	156.080	42	0.025	17
Technology	554.518	2	0.105	2	Activity	147.661	43	0.018	33
Project	482.430	3	0.051	4	Talented Person	147.661	44	0.017	36
Enterprise	424.206	4	0.059	3	China	144.794	45	0.020	27
New Drug	362.651	5	0.034	10	Arts and Crafts	144.437	46	0.018	34
Information	323.184	6	0.046	8	Solution	140.098	47	0.012	57
Research Paper	301.616	7	0.051	5	Wisdom Knowledge	140.015	48	0.002	82
Document	300.674	8	0.023	21	Strategy	137.831	49	0.012	58
Plan	291.122	9	0.019	29	Center	130.492	50	0.016	41
Science and Technology	285.639	10	0.046	7	On-line	128.555	51	0.014	49
Account	282.847	11	0.023	22	Material Science	126.404	52	0.012	61
Medicine	268.921	12	0.028	14	Science	123.944	53	0.014	47
China	262.495	13	0.048	6	Machine	123.794	54	0.007	78
Cost	244.710	14	0.027	16	Funds	122.326	55	0.008	77
Keynote	243.562	15	0.013	51	Global	120.646	56	0.009	73
Product	241.485	16	0.024	20	Industry	119.160	57	0.014	48
Platform	240.823	17	0.031	11	Computer	118.044	58	0.013	52
Mode	231.099	18	0.018	35	Expert	116.755	59	0.008	75
Expenditure	230.836	19	0.015	46	Feasibility	116.210	60	0.004	80
University	228.511	20	0.040	9	College	110.904	61	0.016	38
Automobile	227.051	21	0.024	18	Energy	110.635	62	0.011	68
Traditional Chinese Medicine	224.117	22	0.020	26	Shanghai	110.635	63	0.011	67
Capital	219.775	23	0.017	37	Human Resource	109.888	64	0.013	50
Presentation	205.260	24	0.019	31	Knowledge	109.741	65	0.012	55
Resources	203.983	25	0.029	12	Agriculture	107.602	66	0.011	66
Academic Degree	199.626	26	0.013	53	Economy	107.438	67	0.019	30
Data	198.793	27	0.021	25	Mechanics	107.202	68	0.012	54
Works	194.081	28	0.028	13	Institution	105.079	69	0.012	60
Professional	193.823	29	0.019	28	Important	103.972	70	0.010	71
Intelligence	187.768	30	0.019	32	Foundation	103.020	71	0.016	39
Engineer	186.855	31	0.028	15	Anhui	101.938	72	0.008	74
Master	184.159	32	0.010	69	Preparation	101.938	73	0.007	79
Method	179.280	33	0.024	19	Scientific Research	101.938	74	0.011	64
Software	179.280	34	0.021	24	Wuhan	101.268	75	0.010	70
Biology	179.195	35	0.022	23	Structure	94.830	76	0.011	62
Equipment	169.713	36	0.015	43	Utility	94.605	77	0.011	65
Teaching	165.952	37	0.011	63	Channel	93.575	78	0.004	81
Curriculum	160.803	38	0.012	59	Teacher	90.273	79	0.015	44
Electronics	159.424	39	0.016	40	Environment	89.704	80	0.009	72
Network	158.686	40	0.015	45	Research Center	88.533	81	0.012	56
Food	156.286	41	0.015	42	Academic	87.036	82	0.008	76

Appendix B

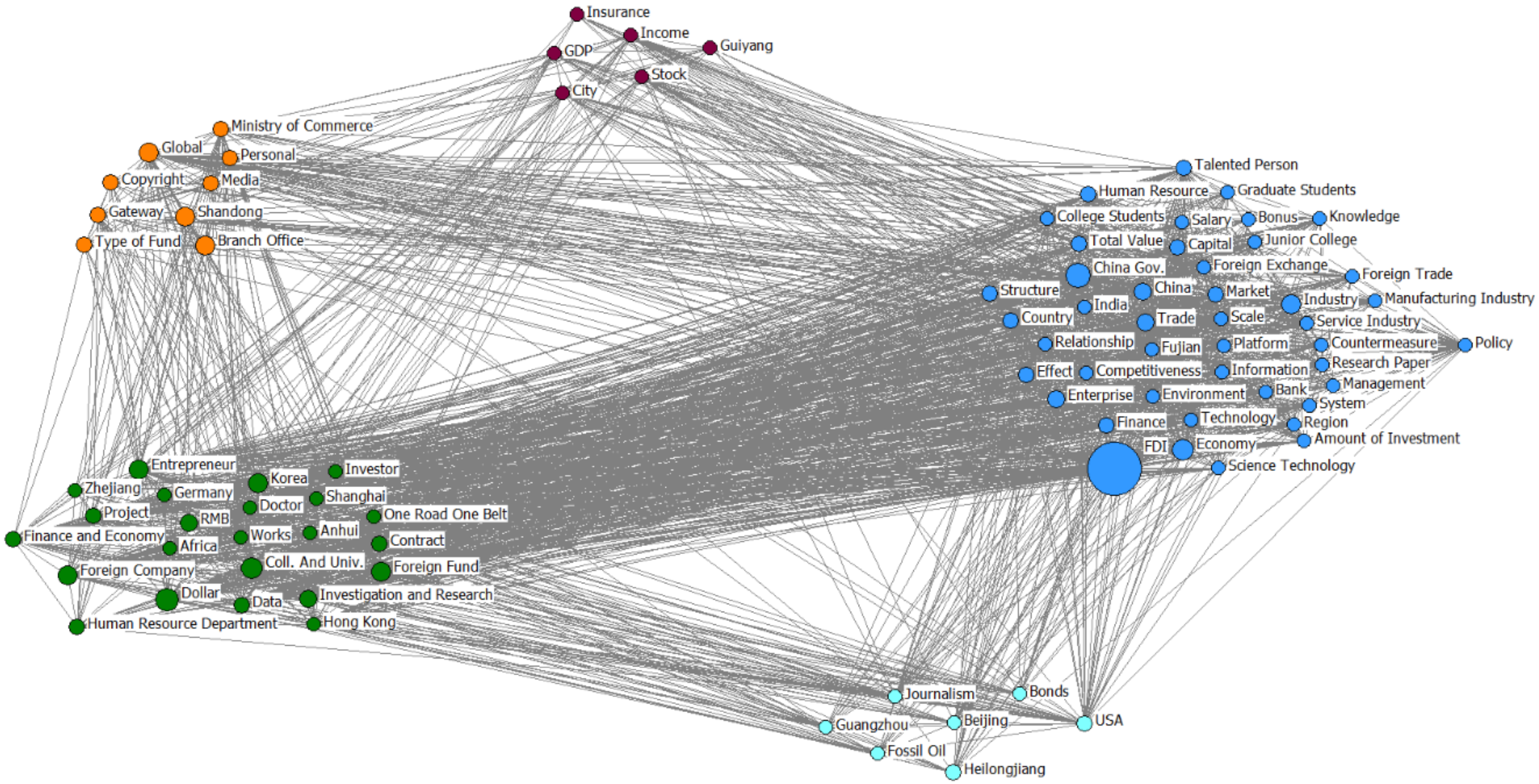

Figure A1. The result of semantic network analysis for FDI.

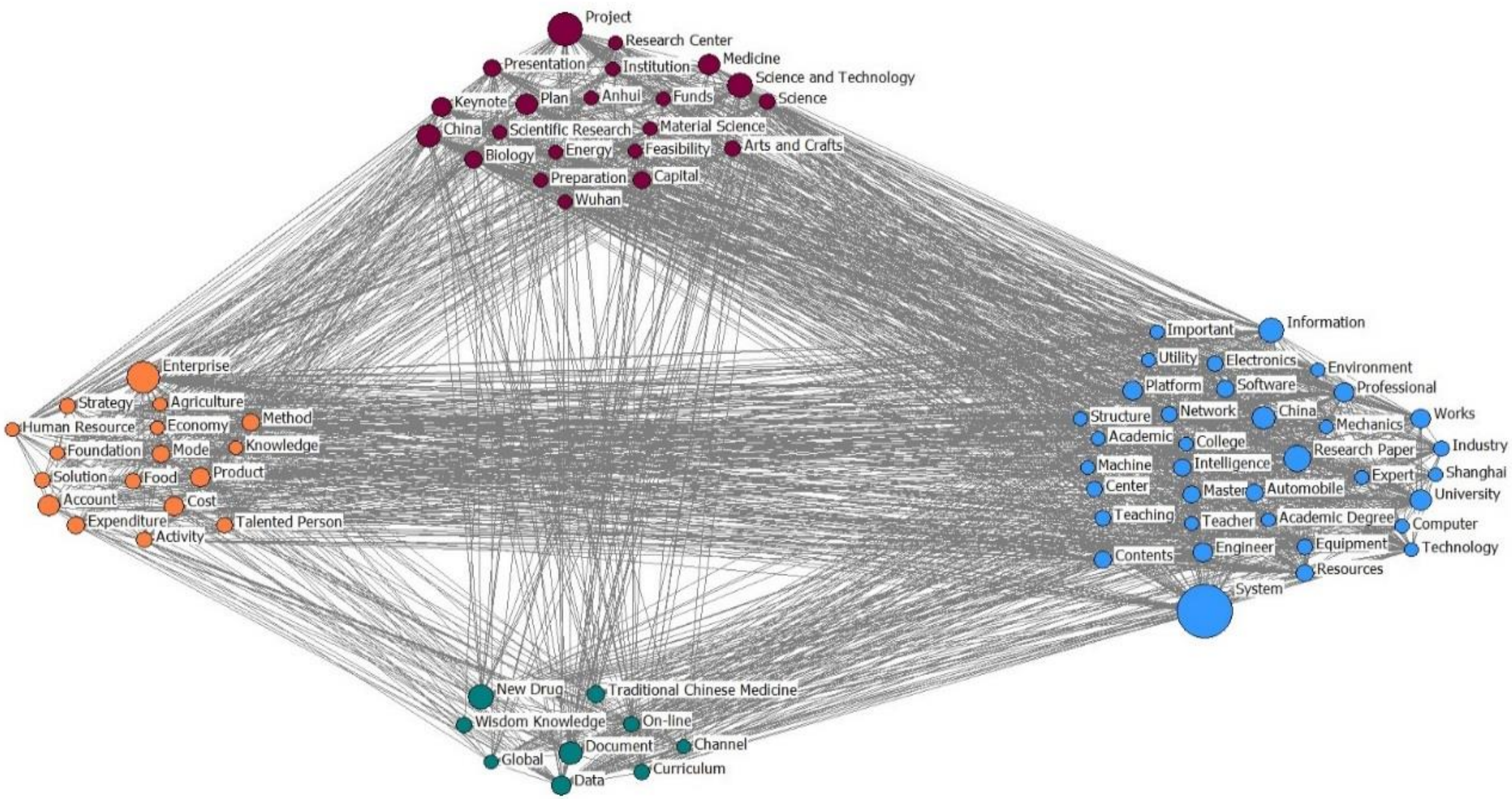

Figure A2. The result of semantic network analysis for R&D.

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