

Article Effects of FDI, External Trade, and Human Capital of the ICT Industry on Sustainable Development in Taiwan

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Abstract: Understanding how international trade, FDI and human capital (*FDI-HC* and *ET-HC*) in the ICT industry affect Taiwan's stable economic growth between 2001 and 2020 is the main objective of this study. The empirical analysis method used in this study is mainly divided into two steps: First, it uses variables with reliability and authenticity as keywords for primary, data mining, and semantic network analysis (SNA). Second, it investigates the long- and short-term interactions between the variables using the vector error correction model (VECM). The results of data mining and SNA using FDI and ET as keywords reveal that terms connected to HC have high levels of centrality, clustering, and frequency. This finding implies that the variables *FDI-HC* and *ET-HC* are reliable and can be utilized as interaction variables. Moreover, FDI–HC and ET–HC exert positive short- and long-term influences on GDP, and ET–HC exerts strong mid- to long-term impacts on GDP, FDI–HC, and ET.

Keywords: external trade–human capital; FDI–human capital; text mining; semantic network analysis; Taiwan economic growth; vector error correction model (VECM)

1. Introduction

In recent decades, societal progress has been influenced by the use of ICT. Countries concentrate on developing the ICT sector to stay up with the digital world of today, eliminate regional barriers, improve communication, simplify corporate processes, and boost economic growth across all sectors [1]. After 2020, the COVID-19 pandemic and AI automation services have affected various industries. In particular, the development of the ICT industry in Taiwan focuses on two major aspects: The first is the industrial environment (e.g., 5G networking and AI popularization of applications) to ensure the continuous reshaping of the digital ecosystem. The second deals with enhancing industrial resilience and modifying the supply chain and product design to hasten the advancement of digital technology, which have a favorable effect on the long-term sustainability of Taiwan's economic influences. Sustainable investment can help a nation evolve and flourish, and many nations prioritize FDI and external trade (ET) for societal advancement. FDI can help a country's economy grow by transferring the successful capital, state-of-the-art technology, management expertise, and intangible assets of enterprises [2,3]. Alternatively, although ET is considered a nationally indispensable factor of sustainable development [4], nearly all countries worldwide have seen much faster growth of import and export flows compared with GDP growth in the past decades. With this trend in trade globalization becoming increasingly stronger, strengthening cooperation among countries is undoubtedly an inevitable process for rapid development [5–9]. In addition to these factors, a notable aspect is the role of soft power, such as human capital (HC), which is an essential element of endogenous growth theory. Along with other important elements that foster growth, such as FDI and ET, it is regarded as having a significant impact on a nation's development. Furthermore, when paired with other growth indices, HC can be a critical component of maintaining sustainable development. The relationship between FDI and HC entails



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). more than just pure funds influx because established knowledge and technology must be introduced to host countries in order to be approved [10]. ET involves many subjects and countries, and HC is strongly correlated to ET. In light of this, inequalities in a country's level of economic development will result from variances in the quantity and quality of HC. The sustainable development of a country should be examined by analyzing the effect of independent (FDI and ET) and interactive (FDI–HC and ET–HC) variables on economic growth. In conclusion, a thorough study of a nation's sustainable development needs to take relevance and dimensions into account.

Taiwan is identified in this study as the nation most able to illustrate the theoretical background of development theory. Taiwan plays a significant role in the global information and communication technology market, and from 1952 to 2022, 25% of all FDI in Taiwan was invested in the ICT sector [11]. The high ratio of the trade values of ICT products in terms of the total trade volume indicates that the competitiveness of Taiwan in international trade is high. In 2020, the total import of ICT commodities reached 10.68 billion USD or an increase of 191% in 2001; the total export value reached 20.38 billion USD or an increase of 255% in 2001 [12]. Financial resources are not the only high-level intangible assets that foreign direct investment (FDI) in Taiwan provides from industrialized countries. Among them include modern technology, marketing expertise, distribution management, leadership of organizations, and management of clients [13,14]. This indicates that FDI can benefit domestic firms in additional ways to promote domestic capital formation, job creation, and economic growth, such as by fostering HC growth and ET advantages [15]. Through ongoing interactions between FDI, ET, and HC, these two FDI-influenced aspects have been contributing to Taiwan's development. FDI, ET, and HC each have independent effects on economic growth in Taiwan and other nations, despite the fact that their correlation and interaction have a significant impact on development [16-21]. In order to overcome this restriction, this study looks at the effects of FDI-HC and ET-HC interactions on economic growth, which is essential for Taiwan's sustainable development.

In designing a research model with interaction variables, we sought originality in both content and process. In other words, we designed a two-step research process that sequentially analyzes unstructured and structured data. Regarding the content, we used SNA to derive variables based on previous research while ensuring the robustness of interaction variables. Through data collection, data cleaning, text mining, and network analysis, SNA validated the possibility of variable interaction. In addition, the VECM was subjected to data collection, sorting, the unit root test, the cointegration test, the Granger causality analysis, and the variance decomposition analysis. These steps enhanced the reliability of the article's originality and the evaluation of the variables' interdependence. This methodological integration of the two-step approach increased the reliability of the article's originality and the assessment of mutual influence among variables by combining these two approaches.

The remainder of this essay is structured as follows. Section 2 offers a theoretical explanation of the effects of FDI, ET, and HC interactions in the ICT industry on Taiwan's economic growth based on previous research. Section 3 introduces the SNA and VECM-based two-step approach paradigm. The data, methods, and analysis results of each stage are presented and explained in detail. Section 4 covers the findings of the two-step study and their implications for policy. Section 5 concludes with a list of limitations.

2. Literature Review

2.1. ICT Industry in Taiwan

In recent decades, the economy in Taiwan has been displaying an upward trend; especially in recent years, it has grown rapidly. In only three years (2019–2022), GDP per capita increased from USD 28,000 to 33,000, mainly depending on the rapid development and progress of the ICT industry. The contribution of the ICT industry to GDP exceeds 80%. In recent years, the added value created by the ICT industry has repeatedly hit new highs, which was driven by the wave of global digitalization and the continuous investment of

the industry in high-value-added products. In 2020, it reached USD 122 billion with a real annual growth rate of 15.7%, which is higher than the overall economic growth rate of 3.36%. The contribution of the ICT industry to economic growth has maintained a positive contribution in the past 10 years (2012–2022); specifically, its contribution in 2020 reached 2.69%, contributing more than 80% to economic growth [12]. However, the sustainable development of the ICT industry will face the important task of digital transformation, and many aspects will require careful consideration, such as the completion of digital transformation and acceleration of the development of the ICT industry. Along with increasing FDI in the ICT industry and increasing the volume of ET, the introduction of talents is also a key point. By adding ICT human resources to high levels of education, the ICT industry will be increasingly innovative and feasible and develop better in Taiwan [22,23]. In addition, the government of Taiwan has established the "five plus two" industry innovation plan (i.e., "smart machinery", "Silicon Valley of Asia", "green energy technology", "biomedical industry", "defense industry", "new agriculture", and "circular economy") to promote innovation and speed up the trend of industry innovation by establishing application services built on the foundation of the current ICT industry [24].

2.2. Sustainable Development and ICT Industry

Endogenous growth theory was created by Romer and Lucas [25,26] and aims to use empirical models to pinpoint the causes of long-term economic growth. Elements that emphasize knowledge acquisition and spillover effects, such as R&D investment, ET, and HC, make sustainable growth possible. Particularly in emerging nations, FDI generates a number of growth drivers that operate as engines for economic expansion. According to the endogenous growth hypothesis, FDI is a sizable potential contributor to economic expansion that raises the marginal productivity of host countries' capital stocks. But an economic environment with active FDI enticement policies is necessary in order to take advantage of the potential of FDI. Significant incentives for attracting FDI in this area include using HC and boosting infrastructure investment.

Without this favorable economic climate, foreign capital may be able to invest more privately, but this may not have a significant impact on the increase in the social returns of the host nations. This conclusion is based on the reality that FDI is insufficient in an unbalanced economic environment to boost these countries' economic levels only through the transfer of certain industries and technologies. As a result, FDI has an impact on economic growth based on the volume and nature of engagement with the host country's HC.

Globalization made the connection between the economies of various countries increasingly close and gradually formed a worldwide market for goods, services, and capital. In this context, FDI and international trade are considered as main factors that influence sustainable economic development. Foreign technology and experience can provide beneficial externalities through FDI in addition to providing direct capital financing [27,28]. Therefore, in theory, FDI increases the host country's productivity and fosters economic growth. However, there is conflicting empirical evidence about the existence of this favorable productivity externality [29]. The macro empirical literature concludes that there is inadequate evidence to substantiate the exogenous beneficial effect of FDI on economic growth. The findings of this study show that local factors, such as the growth of regional financial markets or the overall level of education, may restrict a country's ability to benefit from FDI's externalities. Only transferring HC and technology via FDI is insufficient to raise these nations' economic standing. Due to this, FDI and the HC of host countries might interact, which affects economic growth, particularly in developing countries [30].

The impact of FDI on economic growth has been studied by numerous academics to date. This research can be divided into two groups, positive and negative effects and related to the social environment and level of national development. Kisswani [31] observed that FDI had a favorable effect on economic growth and recommended that appropriate policy choices be made regarding the kind of FDI to draw in. Corradini [32] used panel data from

Italian NUTS-3 regions and the VAR method to study the relationship between formal institutional interventions and sustainable regional development.

Sayari [33] discovered that FDI affects the Index of Economic Freedom (EFI) of Western European countries negatively but not those of Central and Eastern Europe. There may be strategic and global macroeconomic factors behind the adverse differential impact of FDI on Western nations. In addition, scholars examined FDI and HC together. For example, using panel data from 62 Vietnamese provinces and the system GMM, Thanh [34] confirmed that government spending effectively impacts the economic growth in different provinces of Vietnam. By using the VECM, Park [35] examined how FDI and its interaction with HC affected economic growth and demonstrated that the interactive factors have a considerable positive impact. Seshadri [36] demonstrated that human resources as a production factor form the industrial basis of ET. The accumulation of human resources mainly includes two aspects, namely, quantity and quality. The connection between import/export trade and human resources will have a substantial impact on economic growth in this situation. Yimer [37] used an error correction model to study the growth effects of foreign direct investment in Africa from 1990 to 2016. It was found that FDI has a significant positive impact on investment-driven and economy-driven economies, but the short-term impact is not significant in factor-driven economies.

Studies on the connection between import/export commerce and economic growth in the context of economic globalization have concluded that these activities support national economic growth as a crucial component of the national economic system. Additionally, it is a critical tool for guaranteeing the balanced growth of various national economic sectors and the efficient progression of social reproduction. Wong and Maki [38,39] pointed out that ET can effectively stimulate domestic demand, create employment opportunities, promote industrial upgrading, and support sustainable economic development. In addition, Tan [40] proposed that ET can stimulate consumption, compensate for the insufficient allocation of domestic resources, improve production technology, optimize industrial structure, and increase income.

However, rapid economic expansion necessitates both HC's ability to absorb new technology and absorption capacity. The significance of HC and technical education was stressed by Howitt and Mayer-Foulkes [41] as well as Dowrick and Rogers [42]. According to Bankole [43], active domestic ET activities facilitated the efficient transmission of technology through this channel, which resulted in knowledge diffusion in HC. In a recent study, HC factors improved our comprehension of how ET affects growth. Nejati [44] empirically investigated the long-term equilibrium link between the environment and ET in north-south regions. The author offered proof that when ICT imports increase, energy utilization, carbon intensity, and carbon emissions also increase. If ICT is flowing south to south and south to north as opposed to north to other regions, the intensity of the cited indicators will be higher. Intra-regional imports boost ICT and GDP output within the regions, which has a positive scale effect. As interregional imports rise, ICT and GDP production in the region importing ICT would decrease. Teixeira and Fortuna [45] looked at how attempts to emulate a number of wealthy countries affected Portugal's long-term prosperity. The results highlighted the superiority of HC investment over R&D investment and showed the positive benefits of HC, R&D activities, and trade on long-term growth. Many academics have recently examined the connection between trade openness and a country's development. For instance, Sikwila [46] demonstrated through ECM that trade openness is beneficial to economic growth. He undertook this by using time series data from South Africa. Additionally, Radmehr [47] verified that FDI and trade openness have a positive effect on GDP by conducting a cointegration analysis on a panel dataset of 62 nations. Otoo and Song [48] compared wealthy and poor country groups to study the effect of ICT on economic growth. The panel dataset of 123 countries included 45, 58, and 20 high-, middle-, and low-income countries, respectively. Although ICT generally accelerates economic growth in both countries, the scientists found that poorer countries typically gain more from it.

Economic transformation is a process of changing from one mode of production or economic growth to another. Economic development in Taiwan has undergone three transformations, namely, land reform, from agricultural production to industrial production, and from basic industry to high-end industry. Afterward, the industrial structure in Taiwan was further adjusted. The technology-intensive and information industry occupied the leading position in this industrial structure in which ICT was at the forefront. For the rapid development of the ICT industry, researchers highlight the impact of ICT on GDP. For example, Sawang, Anwar, and Ishida [49–51] used the VECM and Autoregressive Distributed Lag (ARDL) to analyze the time series data of South Korea, Pakistan, and Japan, respectively. The authors verified that GDP is positively impacted by ICT investment. Shinha et al. [52] used GMM to examine panel data from 36 developing nations and came to the conclusion that ICT has a beneficial effect on GDP. This research indicates how ICT industry growth can support economic growth in both emerging and developed nations. Table 1 summarizes the results of the brief literature reviews.

Table 1. Result of the literature reviews.

			Vari	ables	
Author	Data	Method	Explanatory Variable	Independent Variables	Key Findings
Kisswani [31]	Estonia (1994 Q1– 2013 Q2)	VECM	GDP	FDI	FDI→GDP (+)
Corradini [32]	Italian NUTS-3 regions	PVAR	GDP	IQI	IQI→GDP (+)
Sayari [33]	36 countries from Eastern, Southeastern, Central, and Western Europe (1997–2014)		GDP	FDI	FDI→EFI (−) in Western European countries
Thanh [34]	sixty-two Vietnamese provinces (2006–2015)	System-GMM	GDP	GINV	GINV→GDP (+)
Park [35]	China (1991–2015)	VECM	GDP	FDI R&D HC FDI–HC R&D HC	$FDI \rightarrow GDP (+)$ $R\&D \rightarrow GDP (+)$ $FDI-HC \rightarrow GDP (+)$ $R\&DHC \rightarrow GDP (+)$
Sikwila [46]	South Africa (1994 Q1–2013 Q4)	ECM	GDP	О	$O \rightarrow GDP(+)$
Radmehr [47]	62 countries (1995–2016)	PMG MG DFE	GDP	O, FDI FD, GE	$O \rightarrow GDP$ (+), FDI $\rightarrow GDP$ (+), FD $\rightarrow GDP$ (+), $GE \rightarrow GDP$ (+)
Otoo and Song [48]	123 countries (2002–2017)	APF	Е	ICT	ICT→GDP (+)
Sawang [49]	South Korea (1993–1995)	VECM	GDP	ICT	ICT \rightarrow GDP (+)
Anwar [50]	Pakistan (1980–2014)	VECM	GDP	FDI ICT	FDI \rightarrow GDP (+) ICT \rightarrow GDP (+)
Ishida [51]	Japan (1980–2010)	ARDL	GDP, EC	ICT	ICT \rightarrow GDP (+), ICT \rightarrow EC (-)
Shinha et al. [52]	36 developing countries (2001–2017)	GMM	GDP	ICT FDI	FDI→GDP (+), ICT→GDP (+)
Shirazi et al. [53]	Asia-Pacific and Middle East Regions (1996–2005)	PCSE	ID	O FDI GDP	$O \rightarrow ID (+), FDI \rightarrow ID (+), GDP \rightarrow ID (+)$
Ahmad [54]	Bangladesh (1943–2004)	VAR VECM	GDP	НС	HC→GDP (+)
Wang [55]	China (1998–2003)	PPR	CGDDP	О	$O \rightarrow CGDDP (+)$ before a threshold point $O \rightarrow CGGDP (-)$ after a threshold point

Table 1. Cont.

		ables			
Author	Data	Method	Explanatory Variable	Independent Variables	Key Findings
Akpolat [56]	13 developed and 11 developing countries (1970–2010)	DOLS FMOLS	GDP	CAP ED LIF	$CAP \rightarrow GDP (+)$ $ED \rightarrow GDP (+)$ $LIF \rightarrow GDP (+)$
Kosztowniak [57]	Poland (1992–2012)	VECM	GDP	GFCF E FDI ET R&D	$\begin{array}{l} GFCF \rightarrow GDP (+), \\ E \rightarrow GDP (+), FDI \rightarrow GDP \\ (+), ET \rightarrow GDP (+), \\ R\&D \rightarrow GDP (+) \end{array}$
Jae-pyo Hong [58]	Korea (1988–2013)	VECM	IGDP	TRDI GRDI PRDI	TRDI→IGDP (+) GRDI→IGDP (+) PRDI→IGDP (+)
Zulkarnaen [59]	11 Asian countries (1984–2011)	OLS	GDP	PR, CR, TL, FDI	$PR \rightarrow GDP (+), CR \rightarrow GDP$ (+), $FDI \rightarrow GDP (+), TL \rightarrow GDP (-)$
Zhang [60]	China (1982–2016)	ARDL	CO ₂	FDI, ST, ER	$\begin{array}{c} \text{FDI} \rightarrow \text{CO}_2 (+), \text{ST} \rightarrow \text{CO}_2 \\ (-), \\ \text{ER} \rightarrow \text{CO}_2 (-) \end{array}$
Simion [6]	Romania (1995–2015)	VECM	GDP	IT, ET, GFCF	IT \rightarrow GDP (+) ET \rightarrow GDP (+) GFCF \rightarrow GDP (+)
Intisar [61]	19 Asian countries (1985–2017)	FMOLS DOLS	GDP GDPPC	FDI TPOP LFP	LFP \rightarrow E (-) in Southern Asia, LFP \rightarrow E (+) in Western Asia, FDI \rightarrow GDPPC (-) in Western Asia FDI \rightarrow GDPPC (+) in Southern Asia, TPOP \rightarrow GDPPC (-)
Fatima [62]	80 countries (1980–2014)	GMM	GDP	О	$O \rightarrow GDP(-)$ in a low level of HCA $O \rightarrow GDP(+)$ in a high level of HCA
Syarifuddin [63]	Indonesian (2000 Q1– 2021 Q2)	LPE	GDP	FDI	FDI→GDP (+) pre-COVID-19
Aneja [64]	Egypt and Guinea (1990–2019)	ARDL	GDP	ТОТ	TOT→GDP (+)
Teixeira and Fortuna [45]	Portugal (1960–2001)	VAR	TFP	R&D, HC	R&D→TFP (+); HC→TFP (+)

SLS = Stage Least Squares, OLS = Ordinary Least Squares, VECM = Vector Error Correction Model, VAR = Vector Auto Regression, DOLS = Dynamic Ordinary Least Squares, FMOLS = Fully Modified Ordinary Least Squares, GMM = Generalized Method of Moments, ECM = Error Correction Model, ARDL = Auto Regressive Distributed Lag, PMG = Pooled Mean Group, MG = Mean Group, DFE = Dynamic Fixed Effect, PCSE: Panel-Corrected Standard Errors, PPR = Pooled Panel Regression, LPE = Low Pitch Eave, HFDI = Horizontal FDI, VFDI = Vertical FDI, ICT = ICT Investment, CAP = Capital Investments, ED = Education Expenditures, LIF = Life Expectancy, GDPPC = GDP Per Capital, TPOP = Total Population, LFP = Labor Force Participation, HCA = Human Capital Accumulation, O = Trade Openness, GFCF = Gross Fixed Capital Formation, E = Employment, IT = Import, ET = Exports, IGDP = ICT Industry, TRDI = Total R&D Investment, GRDI = R&D Investment, PRDI = Private R&D Investment, EC = Energy Consumption, FD = Financial Development, GE = Government Final Consumption Expenditure, ID = ICT Diffusion, PR = Political Rights, CR = Civil Rights, TL = Trade Liberalization, EFI = Economic Freedom Index, CGGDP = Comparable Green GDP, ST = Services Trade, ER = Exchange Rate, TOT = Terms of Trade, TR = Total International Commercial Transactions, TFP = Total Factor Productivity, GDP = Gross Domestic Product, FDI = Foreign Direct Investment, PVAR = Panel Vector Autoregressive, IQI = Institutional Quality Index, GINV = central government investment per capita, R&D = Research and Experimental Development, HC = Human Capital, APF = Aggregate Production Function.

In conclusion, Taiwan can offer a reliable assessment of the effect of FDI and import/export commerce in the ICT industry on GDP growth because it is a developed nation. This impact's importance will be more accurately reflected by how FDI, import/export trade, and the rate of job growth in the ICT sector interact.

3. Materials and Methods

We pre-verified the interrelationships between the variables using SNA prior to conducting an empirical analysis utilizing the VECM in order to strengthen the robustness of the research model and provide sufficient and varied interpretations for it in this study. Therefore, we first used SNA to analyze unstructured data before examining the reciprocal effect, centrality, and structural similarity of the words that the variables imply. By performing a final analysis of the formal data using the VECM, we could examine how the variables interact and serve different purposes.

3.1. Step One: Semantic Network Analysis

Large volumes of unstructured data can be analyzed using the SNA method, which locates interrelated patterns in their nonlinear interactions. According to Lopes et al. [65], SNA, in particular, sees the words obtained through the principal keywords as network nodes and the connections, linkages, and patterns between words as semantic social relations. By analyzing structural factors, we could investigate the context in which a particular keyword is discussed and interpreted in lay and professional discourse [66]. Network theorists claim that, as a result, clusters or patterns that are generated by the frequency, co-occurrence, and centrality of words appearing in the network can be used to examine the meaning conveyed in a text [67,68].

3.1.1. Data

By using Python web crawling and the terms FDI and ET, this study collected data on news and documents from 2015 to 2020 from an online portal. Google, as the world's top search engine, accounts for over 95% of the search market, which makes it the most appropriate channel for exploring the channels of Taiwanese discourse. We collected 1891 and 2788 documents related to FDI and ET, respectively. To standardize and analyze unstructured data, we performed the following procedure. Initially, redundant documents and stopwords were eliminated. Then, through morphological analysis, sentences and words were tokenized. Finally, through the POS tagging process, each word was converted into analyzable data. This allowed us to extract 2530 and 3290 words, respectively. Based on occurrence frequency and degree centrality values, the top 50 words for each term were extracted for SNA.

3.1.2. Text Mining: TF-IDF and Degree Centrality

For the purpose of this study, the TF-IDF and degree centrality were computed using the Python package for Chinese terms. According to assessed centrality and relevance based on phrase frequency and the focal point of linkages between nodes (words or texts) in semantic networks, these classifications are made [69]. Nodes along geodesic pathways between other pairs of nodes are thought to have important places in this network.

The TF-IDF value can be used to extract significant information from unstructured data. This number determines a word's importance within a document using statistical techniques. For example, if a term appears frequently in a work, it can be considered to be important. On the other hand, it can mean that the phrase is widely used. Therefore, a word's value increases in direct proportion to how often it appears in the text; nevertheless, the frequency of the corpus word must be used to balance out the importance of the corpus word [70]. Centrality measures are essential for comprehending networks, which are commonly referred to as graphs. In order to determine the importance of each node in a network, these techniques make use of graph theory. They each operate in a different way, but they all aid in sorting through jumbled data to highlight sections of the network that require attention. Table 2 shows the text mining results of two keywords (FDI and ET).

 Table 2. The result of text mining on FDI/ET of ICT industry.

		Related Words of Human Capital (TF-IDF/Degree Centrality)
Main words	FDI	University (341.170/0.075), Talent (282.347/0.068), Graduate Student (282.347/0.041), Development (235.289/0.053), Human Resources (235.289/0.049), Reports (141.174/0.029),
Wallt Wolds	ET	Information (201.798/0.099), Law Office (137.608/0.045), Service (106.060/0.033), Human Resources (71.223/0.027), Enterprise (59.352/0.027), Reports (55.352/0.019), R&D (40.328/0.032)

Table 2 provides the 50 terms that were chosen as having the highest frequency and importance out of the 2530 words that were found, retrieved, and refined for ET and FDI. First, the study identified phrases relating to FDI (such as University, Talent, Graduate Student, Development, Human Resources, Reports, and Design) that were often and significantly associated with HC. According to this relationship, skilled workers are required to solve local problems throughout the FDI influx process or to utilize FDI once it has arrived. From the perspective of the centrality of words related to FDI, we found that University (5), Talent (6), Graduate Student (13), Development (7), Human Resources (11), and Reports (20) are highly ranked in terms of centrality (Table A1 in Appendix A). These findings show that human resources, such as graduate students, are crucial to the inflow and usage of FDI and that interactions with HC outside of FDI inflow are necessary to accomplish FDI's intrinsic performance.

Second, with ET as the primary word, a total of 3290 related words were gathered for the investigation. Based on frequency, significance, and centrality, the top 50 words were identified. Similar to the findings of the FDI-related word analysis, words connected to HC, like Human Resources and Reports, are likewise scored reasonably highly among ET-related words. Thus, ET and HC cannot be separated. The fundamental tenet of ET is consistent with that of professionals and academics. Therefore, qualitative growth that effectively leverages human resources is just as vital for obtaining ET results as quantitative growth, such as investing in ET. The notable words are Information (4/5), Law Office (6/17), Service (14/20), Human Resources (21/30), Enterprise (23/31), R&D (36/23), and Reports (27/42). The frequency and central connectivity rankings of these words are mostly higher compared with the 50 keywords (top 30; see Table A2 in Appendix A). This finding suggests that HC has a beneficial effect on ET.

3.1.3. Results of SNA

The study employed the convergence of iterated correlations (CONCOR) analysis as a type of SNA. Utilizing UCINET, a co-occurrence matrix of English terms was created utilizing the retrieved unstructured data relevant to the two key challenges (FDI and ET) [71]. Step two compares the row vectors of each node to the CONCOR matrix (correlation or eigenvalue), revealing patterns of relationships [72,73]. In order to find hidden subgroups and examine relationships between groupings, CONCOR analysis is used to reveal semantic clustering across the whole network of the topic [73,74]. In this study, SNA is conducted using a word correlation matrix. We especially use CONCOR analysis to group words together and identify the existence and properties of key clusters. Table 3 displays the results.

Four clusters in SNA connected to FDI were discovered by the study. Because of the tightness with surrounding nodes, the average clustering coefficient is 2.568. It identified six major hub nodes and found three hubs associated with HC (University, Graduate Student, and Talent). Along with the hub node in the cluster, we also discovered two important keywords (Human Resource and Reports) associated with HC. With an average coefficient of 2.243, four clusters are found for ET. The network contained six main hubs, out of which two (Information and Law Office) were related to HC. Furthermore, we found that among the words in the cluster, five keywords have rather strong connections to HC.

	Main Words					
	FDI of ICT Industry	ET of ICT Industry				
Number of clusters	4	4				
Average clustering coefficient	2.568	2.243				
Major hub nodes	Foreign Direct Investment, Information and Communication Technology, China, University, Graduate Student, Talent	Trade, Export, China, Information, Economy, Law Office				
Significant keywords in the cluster (human capital perspective)	University, Graduate Student, Talent, Human Resources, Reports	Information, Law Office, Reports, Human Resources, Enterprise				

Table 3. The result of the CONCOR analysis.

We discovered that phrases associated with advanced skills, such as Talent, University, Graduate Student, and Human Resource, are particularly significant in a number of industries that use FDI, including finance, foreign capital, facilities, foundation, and product. Therefore, when different HC characteristics combine with FDI, it can benefit host nations since HC plays a critical role in optimizing the impact of FDI (Figure A1 in Appendix B). The key ET clusters for HC are words connected to HC (e.g., Law Office, Reports, Human Resources, Enterprise, and Information) and words pertaining to HC's core domains (e.g., Information, Product, Industry, High Tech, and Market). Through ET initiatives, businesses in other clusters are eager to adopt HC in strategic management and manufacturing procedures. Additionally, they tried to maximize ET performance by interacting ET with HC. The findings indicate that for ET to have a beneficial effect on the economic development of the host nation, HC (such as Enterprise and Law Office) must support it. Additionally, the SNA result, which looked at how economic growth affects ET and HC interactions, is more significant than the result of only looking at how investments in ET alone affect economic growth (Figure A2 in Appendix B).

3.2. Step Two: VECM Analysis

Many economic problems are nonstationary; thus, the regression analysis method is very limited. In practical applications, the majority of time series are nonstationary. Typically, the ARIMA is used to eliminate the nonstationary trend contained in a series, such that the model is established after stabilizing the series, such as the autoregressive integrated moving average model. The time series model developed after being changed into a stationary series renders the time series model uninterpretable since the transformed series restricts the range of the economic issues discussed and lacks a distinct economic meaning.

Granger [75] cointegration theory application is another method for modeling a nonstationary series. Even while some economic variables do not form stationary series when viewed individually, their linear combination might. The stable linear combination that goes by the name "cointegration equation" can be thought of as a long-term stable equilibrium association between the variables. Therefore, this study used VECM to examine the relationship between Taiwan's sustainable economic development and the interaction variables (*FDI-HC* and *ET-HC*). We explicitly created a comparative model that includes GDP, FDI, and ET to assess the relative elasticity of the interaction variables.

3.2.1. Data

For data collection, the study used the online dataset provided by the Department of Statistics of Taiwan [76], the Ministry of Labor of Taiwan [77], and the Statistics Department of the Commerce Department of Taiwan [78] to validate the model. The data use the time series from 2001 to 2020, in which statistics related to FDI and ET coexist. *FDI-HC* is a variable that influences both FDI and HC. The ICT industry's FDI value reflects FDI, and the ICT industry's employment growth rate is represented by HC. ET–HC is an interactive

variable between ET and HC. ET refers to the total import and export trade of the ICT industry. FDI, GDP, and ET were measured at constant prices in 2001 using the price index, and an interaction variable was generated by multiplying the two variables. The resulting dataset contained 120 observations in total. The logarithm of all variables was then taken and incorporated into the model.

3.2.2. Methodology

Emirmahmutoglu [79] and Ahmadi [80] presented Monte Carlo data to back up the assertion that the Granger causality test is the procedure that yields the best accurate results for small sample sizes. In the study, this approach [75] based on the vector autoregression (VAR) model was used to investigate the link between *FDI-HC*, *ET-HC*, and economic growth. However, these tests must indicate that the time series variables included in the model are stationary. Invalid statistics for the Granger causality test result if these variables are nonstationary, which violates the data stability criteria for utilizing the VAR model. According to Granger [75], VECM is a model suitable for testing the relationships between these time series variables if the variables are nonstationary and cointegration survives past the initial difference. The equation is expressed as follows when the primary variables are used:

$$\Delta GDP_t = c_1 + \sum_{i=1}^n \alpha_{1i} \Delta GDP_{t-i} + \sum_{j=1}^n \beta_{1j} \Delta FDIHC_{t-j} + \sum_{k=1}^n \gamma_{1k} \Delta ETHC_{t-k} + \phi_1 ETC_{t-1} + \varepsilon_{1t}$$

$$\Delta FDIHC_t = c_2 + \sum_{i=1}^n \alpha_{2i} \Delta FDIHC_{t-i} + \sum_{j=1}^n \beta_{2j} \Delta ETHC_{t-j} + \sum_{k=1}^n \gamma_{2k} \Delta GDP_{t-k} + \phi_2 ETC_{t-1} + \varepsilon_{2t}$$
$$\Delta ETHC_t = c_3 + \sum_{i=1}^n \alpha_{3i} \Delta ETHC_{t-i} + \sum_{j=1}^n \beta_{3j} GDP_{t-j} + \sum_{k=1}^n \gamma_{3k} \Delta FDIHC_{t-k} + \phi_3 ETC_{t-1} + \varepsilon_{3t}$$

where c, α, β , and are the polynomial's coefficients; *n* stands for the ideal lag; ECT_{t-1} is the correction term; and ε_{1t} is the disturbance term. The causality test model from *FDIHC* and *ETHC* to *GDP* is expressed in Equation (1). Equation (1) establishes the shortrun Granger causation from *FDI-HC* and *ET-HC* to GDP if it rejects the null hypothesis $(H_0 : \beta_{1j} = \gamma_{1k} = 0)$. The error correction term's coefficient (ϕ_1) shows how quickly adjustments are made as they approach equilibrium. As a result, the long-term Granger causality is established from right to left if the null hypothesis $(H_0 : \phi_1 = 0)$ is rejected. Similarly, in the causality test model from *ET-HC* and *GDP* (or *GDP* and *FDI-HC*) to *FDI-HC* (or *ET-HC*), then the rejection of the null hypotheses $H_0 : \beta_{2j} = \gamma_{2k} = 0$ and $H_0 : \phi_2 = 0$ (or $H_0 : \beta_{3j} = \gamma_{3k} = 0$ and $H_0 : \phi_3 = 0$) reflects short-run Granger causality from right to left.

3.2.3. Unit Root Test

The stability of a time series was tested using the unit root test of a time series. A time series is nonstationary if it has a unit root. The unit root can be removed from the nonstationary series using the difference approach to create a stationary series. A time series with a unit root typically exhibits clear memory and fluctuation persistence. As a result, the unit root test serves as the foundation for the cointegration relationship existence test. The Augmented Dickey–Fuller (ADF) [81] and Phillips–Perron (PP) [82] tests are two popular approaches for performing the unit root test. The Dickey–Fuller (DF) test, which is exclusively applicable to first-order instances, is extended in the ADF test. The ADF test is applied when a sequence has a high-order lag correlation [83]. The PP unit root test is proposed for the existence of sequence correlation of disturbance terms. In the unit root test, "C," "CT," and "None" are considered. The principle of the ADF inspection model is as follows:

$$\Delta X_t = \sigma X_{t-1} + \sum_{i=1}^m \beta_i \Delta X_{t-i} + \varepsilon_t \tag{1}$$

$$\Delta X_t = \alpha + \sigma X_{t-1} + \sum_{i=1}^m \beta_i \Delta X_{t-i} + \varepsilon_t$$
(2)

$$\Delta X_t = \alpha + \beta t + \sigma X_{t-1} + \Delta X_{t-i} + \varepsilon_t \tag{3}$$

In the ADF inspection model, X_t represents the original time series; ΔX_t represents the first-order differential time series; σ , α , and β are the coefficients of the polynomial; and ε_t stands for the disturbance term. The actual test sequence is Equation (3) \rightarrow (2) \rightarrow (1). If the test rejects the null hypothesis and if the original sequence lacks a unit root, then the sequence is stationary, and the test is stopped.

Table 4 displays the results of the ADF and PP unit root tests of time series data for *FDI*, *ET*, *HC*, *FDI*-*HC*, *ET*-*HC*, and *GDP*. The original assumption is that a unit root exists; that is, accepting the original assumption indicates that a unit root exists in the sequence, which makes it an unstable sequence. However, rejecting the original assumption denotes that no unit root exists, which makes it a stable sequence. The results demonstrate that the original sequence of *GDP*, *FDI*, *ET*, and *FDI*-*HC* accepts the original hypothesis at a significance level of 1%, which indicates that the four original sequences are unstable. Under the constant and trend conditions of the PP test, the original sequence of *HC* rejects the original hypothesis at a significance level of 5%, which denotes that it is stable. Under the constant and trend conditions of the PP test, the original *ET*-*HC* sequence rejects the original hypothesis at a significance level of 5%, which illustrates that it is stable. The first-order difference sequence of the six groups of data rejects the original hypothesis; that is, the six difference sequences are stationary, and the original sequence is a single integer.

Mariahlas			ADF			PP			
variables		С	СТ	None	С	СТ	None		
GDP	Level Δ	$-0.594 \\ -4.012$ ***	-2.807 -3.916 **	6.093 -0.092	-1.000 -6.958 ***	-2.750 -6.487 ***	16.585 -2.011 **		
FDI	Level Δ	-2.555 -4.703 ***	-2.526 -4.523 **	-0.164 -4.846 ***	-2.555 -4.726 ***	-2.526 -4.525 **	-0.150 -4.875 ***		
ET	Level Δ	-1.204 -3.763 **	-2.811 -3.642 *	2.560 -3.400 ***	-1.221 -4.734 ***	-2.744 -4.590 ***	3.959 -3.352 ***		
НС	Level Δ	-0.853 -5.861 ***	-3.419 -5.639 ***	0.402 -5.963 ***	-2.044 -7.281 ***	-4.101 ** -6.822 ***	-0.431 -5.897 ***		
FDIHC	Level Δ	-2.491 -4.267 ***	-2.825 -4.113 **	-0.164 -4.431 ***	-2.538 -8.235 ***	-2.816 -7.722 ***	0.004 -8.051 ***		
ETHC	Level Δ	-1.291 -5.914 ***	-3.202 -5.688 ***	0.151 -6.111 ***	-3.121 ** -6.518 ***	-4.330 ** -5.800 ***	0.993 -6.863 ***		

Table 4. Results of the unit root tests.

Note: The abbreviation ADF stands for the augmented Dickey–Fuller test, while PP represents the Phillips–Perron test. In this context, C refers to a constant, and CT refers to a combination of constant and trend. Additionally, the symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.2.4. Cointegration Test

The cointegration test aims to verify the nonstationary time series, whose premise is the integration of the same order. It is known as first-order integration and can be checked for cointegration, which denotes the presence of a common random trend if the first-order difference series of the original data are stationary. The cointegration test's goal is to establish the existence of a stable equilibrium relationship in a linear combination of a number of nonstationary sequences. Through the unit root test, the six sequences are first-order integrated such that the cointegration test can be conducted. The VECM model is estimated in this work using the Johansen cointegration test [84,85] to assess whether or not a cointegration relationship exists between variables. We estimate Equation (4) and arrive at an estimated value of Γ as $\hat{\Gamma}$ after calculating the proper lag order p. In Equation (4), X_t represents the original time series, ΔX_t denotes the first-order differential time series, δ is a coefficient, and E_t refers to the disturbance term. For continuous variables, the probability that they are an empty matrix is 0. The key to the Johansen cointegration test is to evaluate whether or not the rank of this matrix is notably not zero because it may only be about equal to 0 at most but cannot actually be equal to 0.

$$\Delta X_t = \delta + \sum_{i=1}^p \Delta X_{t-i} + \Gamma X_{t-1} + E_t.$$
(4)

The cointegration test is available in two types, namely, trace and maximum eigenvalue. Both tests are dependent on the eigenvalue of the matrix $\hat{\Gamma}$. The original and alternative hypotheses of the trace test are as follows:

$$H_0: p = r, H_1: r \ge p \ge k$$
, in which $r = \{0, 1, 2, \dots, k-1\}$

The statistics used are $\lambda_{trace} = -T\sum_{i=r+1}^{k} [ln(1-\hat{\lambda}_r)]$, where $\hat{\lambda}_i$ is the characteristic root of $\hat{\Gamma}$ organized from large to small. The trace test examines whether or not the lowest characteristic roots are 0 to use common language. The rank of the square matrix is shown by the linear algebra to be the number of characteristic roots that are not 0. The maximal characteristic root test is a single test that can be thought of as having the following original and alternative hypotheses:

$$H_0: p = r, H_1: p = r+1$$
, in which $r = \{0, 1, 2, \dots, k-1\}$.

The statistics used are $\lambda_{trace} = -Tln(1 - \hat{\lambda}_{r+1})$.

The findings of the cointegration test utilizing the Johansen approach, which simultaneously applies the trace and greatest eigenvalue tests, are shown in Table 5. The trace test findings can reject the cointegration null hypothesis (H_0 : r = 0) at a significance level of 5% and accept the cointegration null hypothesis at the highest level (H_1 : $r \le 1$), which illustrates a cointegration equation below. The result of the largest eigenvalue test rejects the null hypothesis of cointegration (H_0 : r = 0) at the 5% significance level and rejects the null hypothesis of cointegration at the maximum (H_1 : $r \le 1$). The null hypothesis of cointegration (H_2 : $r \le 2$) indicates the existence of two cointegrating equations under the largest eigenvalue test. Therefore, there is a long-term equilibrium correlation between the variables in 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.
Model1	$H_0: r = 0$	42.753 **	35.193	0.006	25.457 **	22.300 **	0.018
	$H_1: r \le 1$	17.296	20.262	0.122	11.643	15.892	0.208
	$H_2: r \le 2$	5.653	9.165	0.219	5.653	9.165	0.219
Mode2	$H_0: r = 0$	64.622 **	35.193	0.000	36.183 **	22.300	0.000
	$H_1: r \le 1$	28.439 **	20.262	0.003	19.379 **	15.892	0.014
	$H_2: r \le 2$	9.061	9.165	0.052	9.061	9.165	0.052

Note: In Model 1, we analyzed the cointegration relationship among GDP, FDI, and ET. Model 2 focuses on the cointegration between GDP, FDIHC, and ETHC. The symbol r represents the number of cointegrating vectors, and we determine the optimal lag as 3 based on SC statistics. The significance levels are indicated by **, representing significance at the 5% levels, respectively.

3.2.5. Causality Analysis Using a VECM

In order to determine whether one time series is the cause of another time series, the Granger causality test was used. The Granger causality test can be used to look into the causes of the variables if the test data are stationary. The Granger causality test can only be carried out once a cointegration relationship between the sequences has been established,

which is necessary if the data being tested are nonstationary, and each sequence is integrated in the same order. The study discovered through earlier studies that each original time series has a unit root and that the first-order difference sequence is absent from the unit root. Additionally, the cointegration equations for Models 1 and 2 exist. Therefore, in this study, nonstationary but integrated time series of the same order are subjected to a VECM-based Granger causality test [66]. The Granger causality test is more susceptible to the duration of the lag period that is chosen, and different lag periods may yield completely different test findings. In real life, the VAR model is typically used to determine the best lag order. The values of AIC or SC are mostly used to determine it; the lower the value, the better. The AIC value is used in this study as a guide to identifying the ideal lag order, which is ultimately found to be 2:

$$\begin{bmatrix} \Delta GDP_t \\ \Delta FDIHC_t \\ \Delta ETHC_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \sum_{i=1}^n \begin{bmatrix} \theta_{11i} & \theta_{12i} & \theta_{13i} \\ \theta_{21i} & \theta_{22i} & \theta_{23i} \\ \theta_{31i} & \theta_{32i} & \theta_{33i} \end{bmatrix} + \begin{bmatrix} \phi_1 \\ \phi_2 \\ \phi_3 \end{bmatrix} [ECT_{t-1}] + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$

In which Δ represents the first difference operator. The Variable c_i and ε_{it} represent intercepts and error terms of each equation for i = 1, 2, 3, respectively. ECT_{t-1} indicates the error correction (in model 1, ΔFDI and ΔET values are substituted for $\Delta FDIHC$ and $\Delta ETHC$, respectively). In the long run, the coefficients on the error correction terms are significant by t-statistics, and there is a relation from the independent variable to the dependent variable. In order to determine the presence of short-run causality, it is necessary to test the joint significance of the coefficients for each independent variable using the F-statistics of the Wald test. If the F-statistic for the explanatory variable is significant, it indicates the existence of a short-run causal relationship between that variable and the dependent variable. In our study, we employed the Granger causality test based on VECM (vector error correction model) to examine the causal relationship between long-run and short-run variables. The results of the causality test are presented in Table 6.

Madala	Dependent			Inferences				
widdeis	Variables		Short Run				Long Run	
		∆GDP	ΔFDI	$\Delta \mathbf{ET}$	∆FDIHC	∆ETHC	∆ECTt-1	
	ΔGDP		7.292 ***	4.910			-4.056 ***	$\text{FDI} \geq \text{GDP}; \text{ET} \neq > \text{GDP}$
Model 1	ΔFDI	0.409		0.220			1.047	$\text{GDP} \neq > \text{FDI}; \text{ET} \neq > \text{FDI}$
	ΔΕΤ	10,591 ***	5.200				0.282	$\text{GDP} \geq \text{ET;}\text{FDI} \neq > \text{ET}$
	ΔGDP				31,159 ***	34,071 ***	-4.367 ***	$FDIHC \geq GDP; ETHC \geq GDP$
Model 2	ΔFDIHC	11,21	13 ***			1.804	-2.962 ***	$GDP \ge FDIHC;$ ETHC $\neq > FDIHC$
	ΔΕΤΗΟ	8.37	9 ***		2.295		2.888 ***	$GDP \ge ETHC;$ FDIHC $\neq > ETHC$

Table 6. Results of the VECM Granger causality test.

Note: In Model 1, we examine the vector error correction model (VECM) relationship among GDP, FDI, and ET. In Model 2, we investigate the VECM relationship between GDP, FDIHC, and ETHC. The symbol \geq indicates that the left side can cause the right side, while \neq > implies that the left side cannot cause the right side. Significance levels are denoted by ***, representing significance at the 1% levels, respectively.

Based on these results, we first considered the long-term equilibrium relationship based on whether or not the estimation coefficient of the error correction term (\emptyset) exerts a negative impact in the previous period (t - 1). The findings demonstrated that *FDI-HC* and *ET-HC* have long-term reciprocal impacts on GDP because the effects of both on GDP are statistically significant (*FDI-HC* > GDP; *ET-HC* > GDP). Therefore, there are no long-term effects of *FDI-HC* and BIP on *ET-HC* or *FDI-HC* and BIP on *FDI-HC*. Furthermore, Granger's short-run causal analysis merely calls for determining if each difference-explaining variable's coefficient is statistically significant. According to the result, FDI-HC and ET-HC influence GDP in the short term (FDI-HC \rightarrow GDP; ET-HC \rightarrow GDP), and FDI-HC and ET-HC interact in the short term (FDI-HC \leftrightarrow ET-HC). In Model 1, there are no long-term impacts between FDI and ET for GDP, but there are short-term effects between FDI and GDP (FDI GDP; FDI ET). We discovered that FDI has a strong long-term effect on GDP growth when FDI interacts with HC by comparing Models 1 and 2. This result illustrates that the sustainable development of a country requires the use not only of HC but also several development factors. The results also suggest that the organic integration of HC and development drivers, such as FDI and ET, is important in the short term.

Table 7 displays the outcomes of the variance decomposition test. This result might support the Granger causal conclusions that were previously discussed. The variance decomposition of forecast error serves as a gauge for the variables' relative weights in the model. First, Model 1 demonstrates that even in the short run, GDP has a significant explanatory power, but that in the long run, R&D has an even stronger explanatory power—13%. While FDI's short-term explanatory power is 93%, its long-term explanatory power increases to 4%. Its growth dynamic declined to 29% over time. The explanatory power of ET, FDI for ET, and GDP gradually weakens over time, increases to 37%, and changes dynamically, respectively. By using Model 2 and the variance decomposition method, we discover that short-term GDP shocks can account for almost all of GDP. In the long run, the contributions of FDI-HC and ET-HC to economic growth are 8% and 57%, respectively (Model 2 in Table 6). Additionally, FDI-HC is largely immune to ET-HC, which fluctuates in the short and long terms. In the long-term, the significance of the FDI–HC and GDP decreases to 45% and increases to 54%, respectively. Finally, the explanatory power of ET-HC decreases to 4% in the long term. FDI-HC and GDP possess strong explanatory powers over time. When combined, the long-term interactive variables have a sizable effect on the interactive variables, FDI, ET, and GDP. According to this study, inflows of human resources affect FDI and ET, which in turn affect the sustainable growth of the economy as a whole.

M 114D 1	Variance	Decompositio	n of GDP	Variance	Variance Decomposition of FDI			Variance Decomposition of ET		
Model 1 Period	GDP	FDI	ET	GDP	FDI	ET	GDP	FDI	ET	
1	100.000	0.000	0.000	7.026	92.974	0.000	15.892	2.265	81.843	
2	85.674	3.042	11.283	20.292	68.824	10.884	17.334	5.483	77.183	
3	83.275	3.989	12.736	27.759	56.426	15.815	35.247	9.697	55.056	
4	82.898	3.989	11.532	32.388	44.963	22.649	26.981	30.218	42.800	
5	81.785	4.558	13.658	34.845	39.512	25.643	27.023	30.401	42.576	
6	81.780	4.520	13.700	38.152	35.299	26.549	26.225	32.390	41.385	
7	82.920	4.124	12.957	39.996	33.228	26.776	26.005	33.396	40.599	
8	82.923	3.662	13.415	41.050	31.747	27.203	25.795	33.607	40.599	
9	82.988	3.671	13.341	41.952	30.476	27.571	25.047	35.290	39.664	
10	83.271	3.533	13.196	42.487	29.393	28.120	23.826	37.358	38.817	
	Variance Decomposition of C									
Madal 0 Daria d	Variance	Decompositio	n of GDP	Variance D	Decomposition	of FDIHC	Variance I	Decompositio	n of ETHC	
Model 2 Period	GDP	Decompositio FDIHC	n of GDP ETHC	Variance D GDP	Decomposition FDIHC	of FDIHC ETHC	Variance I GDP	Decomposition FDIHC	n of ETHC ETHC	
Model 2 Period	Variance GDP 100.000	Decompositio FDIHC 0.000	n of GDP ETHC 0.000	Variance D GDP 35.231	Decomposition FDIHC 64.769	of FDIHC ETHC 0.000	Variance I GDP 32.350	Decomposition FDIHC 6.640	n of ETHC ETHC 61.010	
Model 2 Period	Variance GDP 100.000 94.419	Decompositio FDIHC 0.000 0.540	n of GDP ETHC 0.000 5.041	Variance D GDP 35.231 49.227	Pecomposition FDIHC 64.769 50.543	of FDIHC ETHC 0.000 0.230	Variance I GDP 32.350 31.296	Decomposition FDIHC 6.640 33.290	n of ETHC ETHC 61.010 35.414	
Model 2 Period	Variance 1 GDP 100.000 94.419 84.732	Decompositio FDIHC 0.000 0.540 0.956	n of GDP ETHC 0.000 5.041 14.312	Variance D GDP 35.231 49.227 48.248	Decomposition FDIHC 64.769 50.543 50.522	of FDIHC ETHC 0.000 0.230 1.231	Variance I GDP 32.350 31.296 34.767	Decomposition FDIHC 6.640 33.290 37.548	n of ETHC ETHC 61.010 35.414 27.686	
Model 2 Period	Variance 1 GDP 100.000 94.419 84.732 74.788	Decompositio FDIHC 0.000 0.540 0.956 1.854	n of GDP ETHC 0.000 5.041 14.312 23.358	Variance D GDP 35.231 49.227 48.248 48.757	Decomposition FDIHC 64.769 50.543 50.522 50.136	of FDIHC ETHC 0.000 0.230 1.231 1.108	Variance I GDP 32.350 31.296 34.767 39.250	Decomposition FDIHC 6.640 33.290 37.548 41.437	n of ETHC ETHC 61.010 35.414 27.686 19.313	
Model 2 Period 1 2 3 4 5	Variance GDP 100.000 94.419 84.732 74.788 64.945	Decompositio FDIHC 0.000 0.540 0.956 1.854 2.599	n of GDP ETHC 0.000 5.041 14.312 23.358 32.456	Variance D GDP 35.231 49.227 48.248 48.757 54.020	Decomposition FDIHC 64.769 50.543 50.522 50.136 45.116	a of FDIHC ETHC 0.000 0.230 1.231 1.108 0.864	Variance I GDP 32.350 31.296 34.767 39.250 57.925	Decomposition FDIHC 6.640 33.290 37.548 41.437 35.010	n of ETHC ETHC 61.010 35.414 27.686 19.313 7.066	
Model 2 Period 1 2 3 4 5 6	Variance GDP 100.000 94.419 84.732 74.788 64.945 58.483	Decompositio FDIHC 0.000 0.540 0.956 1.854 2.599 2.992	n of GDP ETHC 0.000 5.041 14.312 23.358 32.456 38.525	Variance D GDP 35.231 49.227 48.248 48.757 54.020 53.542	Decomposition FDIHC 64.769 50.543 50.522 50.136 45.116 45.602	of FDIHC ETHC 0.000 0.230 1.231 1.108 0.864 0.856	Variance I GDP 32.350 31.296 34.767 39.250 57.925 58.866	Decomposition FDIHC 6.640 33.290 37.548 41.437 35.010 35.741	n of ETHC ETHC 61.010 35.414 27.686 19.313 7.066 5.393	
Model 2 Period 1 2 3 4 5 6 7	Variance GDP 100.000 94.419 84.732 74.788 64.945 58.483 55.834	Decompositio FDIHC 0.000 0.540 0.956 1.854 2.599 2.992 3.652	n of GDP ETHC 0.000 5.041 14.312 23.358 32.456 38.525 40.514	Variance D GDP 35.231 49.227 48.248 48.757 54.020 53.542 53.049	Decomposition FDIHC 64.769 50.543 50.522 50.136 45.116 45.602 46.064	of FDIHC ETHC 0.000 0.230 1.231 1.108 0.864 0.856 0.886	Variance I GDP 32.350 31.296 34.767 39.250 57.925 58.866 57.943	Decomposition FDIHC 6.640 33.290 37.548 41.437 35.010 35.741 36.802	n of ETHC ETHC 61.010 35.414 27.686 19.313 7.066 5.393 5.255	
Model 2 Period 1 2 3 4 5 6 7 8	Variance GDP 100.000 94.419 84.732 74.788 64.945 58.483 55.834 46.074	Decompositio FDIHC 0.000 0.540 0.956 1.854 2.599 2.992 3.652 4.389	n of GDP ETHC 0.000 5.041 14.312 23.358 32.456 38.525 40.514 49.537	Variance D GDP 35.231 49.227 48.248 48.757 54.020 53.542 53.049 53717	Decomposition FDIHC 64.769 50.543 50.522 50.136 45.116 45.602 46.064 45.415	of FDIHC ETHC 0.000 0.230 1.231 1.108 0.864 0.856 0.886 0.886 0.868	Variance I GDP 32.350 31.296 34.767 39.250 57.925 58.866 57.943 56.767	Decomposition FDIHC 6.640 33.290 37.548 41.437 35.010 35.741 36.802 38.298	n of ETHC ETHC 61.010 35.414 27.686 19.313 7.066 5.393 5.255 4.935	
Model 2 Period 1 2 3 4 5 6 7 8 9	Variance GDP 100.000 94.419 84.732 74.788 64.945 58.483 55.834 46.074 37.358	Decompositio FDIHC 0.000 0.540 0.956 1.854 2.599 2.992 3.652 4.389 7.081	n of GDP ETHC 0.000 5.041 14.312 23.358 32.456 38.525 40.514 49.537 55.561	Variance E GDP 35.231 49.227 48.248 48.757 54.020 53.542 53.049 53717 53.968	Decomposition FDIHC 64.769 50.543 50.522 50.136 45.116 45.602 46.064 45.415 45.202	of FDIHC ETHC 0.000 0.230 1.231 1.108 0.864 0.856 0.886 0.886 0.868 0.829	Variance I GDP 32.350 31.296 34.767 39.250 57.925 58.866 57.943 56.767 56.935	Decomposition FDIHC 6.640 33.290 37.548 41.437 35.010 35.741 36.802 38.298 38.782	n of ETHC ETHC 61.010 35.414 27.686 19.313 7.066 5.393 5.255 4.935 4.935 4.283	

 Table 7. Results of the variance decomposition test.

4. Discussion

Sustained economic development requires material and human resources. Material resources form the basis of the survival and development of human society, and capital at home and abroad is the main driving force of economic growth. Technology is the primary productive force, and human resources are the carrier of technology; therefore, human

resources comprise a special element for promoting economic growth. Human resources do not only refer to renewable and sustainable resources but also capital resources. As a result, both domestic and foreign capital, as well as top-tier human resources, have a significant impact on sustainable economic development.

In the 1950s, Taiwan conducted relatively extensive fiscal, external trade, financial system reforms, and human resource development received great attention. In the 1960s and 1970s, the world became multi-polarized, the international situation tended to ease, developed countries transferred labor-intensive industries, labor-intensive industries in Taiwan developed rapidly, and importance was attached to the development of science and technology, and the slogan of technical upgrading was put forward. After the mid-to late-1980s, the trend of globalization of the multi-polar economy worldwide further accelerated, and the international situation improved. Taiwan is actively promoting economic reforms and deepening the market economy. Taiwan places talent training in a priority position, vigorously adjusts the educational structure, strengthens vocational and technical education and training, implements overseas talent exchange programs, promotes industrial upgrading, and achieves sustainable economic and social development.

The world will see increased active investment in digital transformation technology in 2022, when spending on ICT industry business practices, products, and organizations is expected to reach 1.8 trillion USD, up 17.6% from 2021. This prediction comes from the most recent survey report from International Data Corporation (IDC). This expenditure is also expected to continue to rise through 2026. All will maintain this growth rate, which indicates that investment related to global digital transformation will increase in the future. Infrastructure, back-end support, smart manufacturing, and digital supply chain optimization, the three main priorities of the digital transformation in 2022, would cost more than USD 620 billion (or over NTD 1.84 trillion), according to the report. From an industrial standpoint, manufacturing will represent over 30% of the total spending on digital transformation in the world in 2022, followed by professional services and retail.

Digital transformation is a global industry trend and will become increasingly important in the post-epidemic era. Especially in recent years, the global situation has been turbulent, and the new order of the supply chain has been completely rewritten. The basis of the supply chain layout has also changed from reducing costs to reducing risks. Building a more resilient supply chain, such as the cultivation and introduction of professional talents, ET, and FDI, has also become the most important issue in the ICT industry at present. FDI and ET can interact with HC and exert greater impacts on economic growth. From 2000 to 2020, Taiwan's GDP increased by nearly 96.39%. Although the development of a country requires material resources, the most important aspect is, in fact, human resources. However, it takes time for it to mature. As a result, we use a two-step methodology (SNA and VECM) to examine the effects of physical resources (FDI and ET) and human capital (HC) on economic growth.

This study has several implications. First, several networks connected to HC have been created in Taiwan as a result of increasing FDI and ET in the ICT sector. Previous studies typically only explored the impact of a single variable on economic development, such as FDI, ET, total factor productivity, and digital transformation. Moreover, even the results of some studies were not clear [33], thereby ignoring the need to combine the extremely important element of HC [35]. This finding serves as a reminder to keep HC in mind when examining how FDI and ET affect overall economic growth. Particularly in nations like Taiwan, which are undergoing the digital transformation from the conventional manufacturing industry to the growth of the ICT industry, the significance of HC has been rising [86–88]. In other words, opportunities for stimulating domestic education increased, more high-quality HC flowed into the market, and labor resources were effectively utilized. In particular, previous research concluded that economic development was significantly correlated with FDI and ET. According to SNA, advanced talent is crucial to FDI and ET, which emphasizes the significance of its function. According to the findings, which are viewed from the perspective of absorptive capacity, the two main issues that restrict eco-

nomic growth are a lack of technology and the cultivation and education of HC, regardless of the levels of focus and spending on FDI and ET. In light of the SNA's findings, when paired with HC, Taiwan should continue to pursue FDI and ET input policies as well as efficiency and efficiency optimization strategies.

Second, Taiwan experienced rapid industrialization and an export-oriented development model prior to the year 2000. During this time period, the manufacturing and electronics industries became the economic backbone of Taiwan. Taiwan's ICT industry began to develop rapidly after the year 2000.

The VECM findings show that Taiwan's post-2000 economic reform was largely successful. Four financial reforms were started in Taiwan in 2002, 2004, 2008, and 2018, successively. In terms of introducing foreign capital into the capital market, Taiwan also adopted a step-by-step approach. Financial liberalization gradually became popular in the international community. Taiwan also strengthened the opening up of the ICT industry, increased trade openings, and promoted economic growth. Economic development is inseparable from HC. The combination of high-quality talents and material resources can accelerate economic development and the growth of ICT industry competitiveness in Taiwan and enhance its comprehensive economic strength and technological competitiveness. Under the influence of inflation and economic downturn, more than half of enterprises worldwide are facing a serious shortage of talent and technologies. At the same time, enterprises are also facing the pressure of increased operating costs. Thus, the ICT industry can become an important investment for enterprises to solve these pressures. Although the pandemic is gradually dissipating, problems, such as labor shortages, supply chains, and market inflation, continue to exist. Small- and medium-sized enterprises require clear digital strategies, planned technology layouts, and effective internal governance systems if they want to survive or even stand out. Under the consideration of limited funds, improving services and customer experience and enhancing operational flexibility and market competitiveness through digital transformation solutions in the manufacturing industry will be important technological investments for small- and medium-sized enterprises under economic pressure. Taiwan has attached great importance to education a long time ago, which has generally improved the cultural and technological literacy of the population and the labor force. Therefore, continuing to strengthen talent education and investment planning in ICT is necessary in the present and future, such that industrial advantages in Taiwan over the world will become recognizable. Undoubtedly, the results of the statistical analysis demonstrate the endogeneity of all variables used in the research model. This is primarily influenced by Taiwan's ICT promotion policy; the production-logistics-export market environment; and the intricate international relations between the United States, China, and Taiwan. The incorporation of interaction variables proved instrumental in mitigating the process of endogeneity and accounting for national characteristics. In terms of ET, human resources form the factors that require consideration, and the two influence each other to a certain extent. As a strategy for allocating resources across borders, foreign trade will prompt the reallocation of HC investment. Whether it is the active technological innovation brought about by the effect of foreign trade competition or the passive absorption of international technological frontiers, it will promote the accumulation of HC, which can alter the comparative advantage and further influence foreign trade in Taiwan. Therefore, foreign trade and HC can interact and jointly influence economic development. Since 2000, the scale of ET in Taiwan has continued to expand, and the level of HC stock has also improved to a certain extent, which has become an important driving force for the economy in Taiwan to achieve sustained, steady, and medium-to-high-speed growth. From the policy perspective, a long-term plan should be formulated to promote the growth of ET in the ICT industry, which, thereby, promotes sustainable economic development. Introducing outstanding foreign talents and offering relatively high remuneration and benefits in terms of salary are also key points that foreigners highlight when leaving their hometown. After all, a high salary is an important indicator of competitiveness, which attracts foreign talents to work in the ICT industry in Taiwan. The increased demand for

ET can encourage the investment and training of human resources, thereby enhancing the quality and skills of the labor force. Additionally, high-quality human resources can boost the international competitiveness of enterprises and promote the development of ET.

Alternatively, providing guarantees and support in terms of medical health and lowcost medical insurance services for foreigners is also necessary. Foreigners in Taiwan currently need to pay higher medical expenses than the natives if they become sick, such that providing medical insurance for foreign talents working in Taiwan is a crucial factor in attracting them. Based on these implications, the richness of human resources should be enhanced in foreign trade. Taken together, ET and HC play an important role in Taiwan's economy. ET promotes economic growth, industrial upgrading, and market expansion, whereas superior HC serves as a foundation for innovation and competitiveness. These two factors reinforce one another and promote the economic growth and transformation of Taiwan.

5. Conclusions

This study, which is based on the literature on endogenous economic development, looks at the factors that drive the national economy—FDI, ET, and HC interactions—and how they affect GDP as a measure of sustained economic growth. First, by using data mining to determine the degree of word association with HC, network analysis was used to find word clusters associated with FDI, ET, and HC. The outcome demonstrates the relevance and significance of HC in FDI and ET investment. Therefore, the interaction factors, along with HC, should be used to analyze the effects of FDI and ET on sustainable economic development.

Second, VECM was used to look at how FDI and ET interact with HC based on the findings of SNA. The outcomes are contrasted with models (GDP-FDI-ET) that do not include the HC element. Both in the short and long terms, *FDI-HC* and *ET-HC* have positive (+) effects on GDP growth. In particular, the interaction between R&D and HC exerts a significant effect on GDP growth compared with FDI–HC. This conclusion suggests that for the country's continuous development and for the creation of an environment in which they can carry out their work and produce results, it is essential to develop high-quality human resources in the ICT industry. Additionally, there is reciprocity between *FDI-HC* and *ET-HC* interactions, which can be seen as a complementary relationship between FDI, ET, and HC that may promote national development.

The results are of practical academic significance. First, when analyzing the impact on economic and social development, two key elements, namely, FDI and ET, and, importantly, their interaction with HC, should be considered. Second, unstructured data, such as text data, should be used for analyzing the impact on economic growth. Such data contain a large amount of data and great value. Text keyword retrieval can be achieved through data mining and SNA. Third, economic growth and sustainable economic development can be achieved by increasing FDI and ET. Finally, an urgent need emerges to improve HC, improve the level of education, and introduce talents. Improving the HC level is a decisive factor in promoting the transformation and upgrading of the ICT industry and is conducive to promoting high-quality and sustainable economic development.

Despite its practical significance, the study has its limitations. First, the variables used ignore the spillover and crowding-out effects. If empirical analysis of these effects can be conducted on these variables, then decision-makers may point to the positive impact on economic growth, pay attention to risk prevention, and propose comprehensive laws, regulations, and policies. Second, in the process of selecting the variables, we were unable to consider grouping HC into subcategories. When examining the sustainable development of an economy, the interaction among variables should be considered due to the complexity of factors that influence economic growth. After highlighting the interaction between the variables and HC, we can consider the interaction, and the proportion of talents in the ICT industry. Finally, it is necessary to recognize the limits of data and methodology. In the

context of unstructured data, comprehensive utilization of government policy documents and academic data would be advantageous for achieving more meaningful analysis. In addition, incorporating panel analysis techniques that take industry and region into account can yield more nuanced and substantial implications.

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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)) [69]:

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

in which $tf_{x,y}$ denotes the frequency of x in y, df_x denotes the number of documents containing x, and 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) [89]:

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

in which $C_D(N_i)$ denotes the degree centrality of node *i*, *g* is the number of nodes, and $\sum_{j=1}^{g} x_{ij}$ indicates the number of connections that node *i* has with the (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)):

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

Words	TF-IDF	Rank	Degree Centrality	Rank	Words	TF-IDF	Rank	Degree Centrality	Rank
Foreign Direct Investment	941.138	1	0.238	1	Information	94.116	26	0.079	4
Information and Communication technology	611.752	2	0.131	2	Taiwan	93.956	27	0.019	36
China	482.343	3	0.088	3	Finance	87.874	28	0.050	10
University	341.170	4	0.075	5	Electronics	86.381	29	0.021	29
Graduate Student	282.347	5	0.041	13	EU	86.371	30	0.022	28
Talent	282.347	6	0.068	6	Firm	82.355	31	0.026	26
Development	235.289	7	0.053	7	Impact	82.351	32	0.031	19
Human Resources	235.289	8	0.049	11	International	79.552	33	0.023	27
Economy	223.525	9	0.051	9	Construction	76.587	34	0.020	33
Korea	211.760	10	0.026	25	Currency	74.321	35	0.012	46
Information	190.204	11	0.029	20	Germany	71.543	36	0.015	44
Market	164.703	12	0.034	16	Internet	70.587	37	0.021	30
Service Industry	155.535	13	0.048	12	Southeast Asia	70.587	38	0.013	45
Country	152.938	14	0.041	13	Telecom	70.224	39	0.011	48
Technology	152.528	15	0.034	16	Active	69.855	40	0.017	38
Reports	141.174	16	0.029	21	Business	68.822	41	0.020	34
Thailand	129.426	17	0.019	35	Design	67.722	42	0.016	43
Trade	129.419	18	0.035	15	Equipment	65.822	43	0.017	39
Global Company	126.689	19	0.052	8	Facilities	65.522	44	0.017	40
Amount	118.980	20	0.027	23	Foundation	63.822	45	0.017	41
Field	105.888	21	0.031	18	Plan	62.653	46	0.017	42
Foreign Countries	105.882	22	0.027	23	Product	62.653	47	0.021	31
Review	105.882	23	0.020	32	Supervision	58.650	48	0.012	47
Bank	99.196	24	0.029	22	United States	56.335	49	0.011	49
Foreign Capital	94.116	25	0.017	37	Western Asia	56.229	50	0.010	50

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

Table A2. The results of the relative term frequency and centrality for ET.

Words	TF-IDF	Rank	Degree Centrality	Rank	Words	TF-IDF	Rank	Degree Centrality	Rank
Trade	593.524	1	0.193	1	Market	55.352	26	0.029	26
Export	242.559	2	0.178	2	Reports	55.352	27	0.019	42
China	201.798	3	0.076	6	Situation	52.355	28	0.029	27
Information	201.798	4	0.099	5	System	52.240	29	0.029	28
Economy	142.446	5	0.072	7	Total	48.624	30	0.019	43
Law Office	137.608	6	0.045	17	Business	47.482	31	0.023	35
International	135.575	7	0.061	9	Continental	47.482	32	0.033	21
Product	132.808	8	0.049	15	Country	46.920	33	0.026	32
Taiwan	130.575	9	0.030	24	Impact	46.120	34	0.022	38
Science and Technology	121.614	10	0.104	3	Smart City	44.288	35	0.016	45
United States	118.705	11	0.051	12	R & D	40.328	36	0.032	23

Words	TF-IDF	Rank	Degree Centrality	Rank	Words	TF-IDF	Rank	Degree Centrality	Rank
Development	106.834	12	0.069	8	Analysis	38.476	37	0.053	11
Imports	106.321	13	0.051	13	Bank	37.611	38	0.022	39
Services	106.060	14	0.033	20	Chinese	37.611	39	0.015	46
Signal Communication	105.516	15	0.104	4	Communication	37.611	40	0.025	34
Industry	94.964	16	0.054	10	Estimated	35.644	41	0.008	49
Information and Communication Technology	90.841	17	0.048	16	Ma Ying-Jeou	35.611	42	0.015	47
Technology	87.356	18	0.050	14	High Tech	35.525	43	0.008	50
Electronics	83.093	19	0.045	18	Overall	34.611	44	0.023	36
Foreign Direct Investment	80.605	20	0.033	20	Production	34.142	45	0.020	40
Human Resources	71.223	21	0.027	30	Society	34.142	46	0.026	33
Korea	65.880	22	0.017	44	Tariff	33.611	47	0.020	41
Enterprise	59.352	23	0.027	31	Trump	33.440	48	0.015	48
Equipment	59.352	24	0.022	37	Cooperation	32.825	49	0.037	19
Investment	57.004	25	0.026	31	Commodity	31.487	50	0.028	29

Table A2. Cont.

Appendix **B**



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



Figure A2. The result of semantic network analysis for ET.

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