economies

Article

Intellectual Capital and Technology as Factors of Career Success: Role of Income Inequality

Taiwo T. Lasisi [1,*], Elena I. Lazareva [1], Gor A. Abramyan [1], Julia V. Gavrilova [1] and Anton D. Murzin [2]

[1] Department of Innovation and International Management, Southern Federal University, 344006 Rostov-on-Don, Russia
[2] Department of Spatial Economic Systems Development Management, Southern Federal University, 344006 Rostov-on-Don, Russia
* Correspondence: ttlasisi@gelisim.edu.tr or lasisi@sfedu.ru

Abstract: The United Nations Sustainable Development Goals (UNSDGs) elaborately promote "sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all" (Goal 8: SDGs). Considering that there has not been any cross-country comparison of the role of intellectual capital in career success, this study examines the nexus between intellectual capital and career success through the channels of income inequality, information, and communication technology from 1997 to 2018 for six European Economic Area (EEA) countries with high human development index (HDI). Using the Pooled Mean Group Autoregressive distributive lag model, results show that there is a positive and linear relationship between intellectual capital, income inequality, information and communication technology, and career success in the long run. Findings from the causality test reveal there is one-way causality running from information and communication technology and career success as well as intellectual capital to career success. These findings suggest that intellectual capital is important for career success; therefore, policymakers need to invest in developing and improving intellectual capital to ensure objective career success among the nationals.

Keywords: career success; technology; PMG-ARDL; income inequality; intellectual capital

Citation: Lasisi, Taiwo T., Elena I. Lazareva, Gor A. Abramyan, Julia V. Gavrilova, and Anton D. Murzin. 2023. Intellectual Capital and Technology as Factors of Career Success: Role of Income Inequality. *Economies* 11: 63. https://doi.org/10.3390/economies11020063

Academic Editor: Joydeep Bhattacharya

Received: 26 November 2022
Revised: 13 January 2023
Accepted: 17 January 2023
Published: 14 February 2023

1. Introduction

The subject of sustainability continues to gain attention because of the United Nations Sustainable Development Goals (SDGs) 2030 agenda that was launched in 2015. It concludes with universal and global indicators for international cooperation as well as collaboration with the private sector, multilateral institutions, civil society, and governments (Secundo et al. 2020). The SDGs aim to find effective solutions and multidisciplinary approaches to some complex issues and challenges such as food security, ecosystem resilience, migration, pollution, climate change, energy, etc. (Birtchnell et al. 2017). Following this discourse, some scholars have considered human development (Waldmüller et al. 2019) and intellectual capital (Suciu and Năsulea 2019) as important links needed to fulfill the SDGs. Studies such as (Suciu and Năsulea 2019) have maintained that intellectual capital is the most important and prevailing driver of inclusive, sustainable, smart social and economic development. Achieving sustainability is dependent on social innovations and technology (Sheikh 2021), and a relationship between social innovation has been linked with intellectual capital (Sheikh 2021) and employability (which results in career success) (van der Heijde and van der Heijde and van der Heijden 2014).

Intellectual capital, within the modern knowledge economy (Cinquini et al. 2012), indicates the transition to competitive, innovative, and sustainable development (Martins et al. 2019). People are considered the "engine" of sustainable development growth because the skills they possess are crucial resources to the economy. Intellectual capital is a set of proficiencies and experiences of employees in an organization/country, which has the potential for long-term profit for the organization/company (Alvino et al. 2020). Intellectual capital helps in long-term value creation (Ali and Anwar 2021) which is crucial for sustainability (Ali and Anwar 2021) in the furtherance of people's well-being and economic development which is in line with the sustainable development goals.

Technology plays an important role in knowledge dissemination (Cinquini et al. 2012) because it helps in maximizing the exchange of information (Bhatti et al. 2021). Furthermore, knowledge mobilization in all sectors of environmental, economic, and social spheres has become a very important tool that also helps in the creation of a more sustainable future. Technology also increases employee productivity (Al-Nashmi and Amer 2014) as well as seeking strategic solutions that consider sustainability to ensure competitive advantage. To promote sustainable and inclusive economic growth, the role of technology and technology access cannot be neglected because it helps in integrating expertise and information, thereby increasing profitability (Arias-Pérez et al. 2021).

Considering that the human development index (HDI) is one of the more complex composite assessments of the level of human potential and quality of life, this study fills the gap in the literature by contributing to the theory of intellectual capital by exploring a cross-country investigation of the relationship between intellectual capital, technology, income inequality, and career success of six countries (Norway, Iceland, Germany, Sweden, Denmark, and the Netherlands) ranked as countries with very a high human development index (HDI) by United Nations Development Programme (UNDP) (United Nations Development Programme Reports and Publications 2021). Several studies have been carried out to determine the antecedents of career success and factors such as social capital, human capital, and career capital competence were revealed (Guo et al. 2012; Valk et al. 2014); however, these studies have carried out the study using primary data and have not considered this at a national level. Furthermore, previous studies on intellectual capital and career success have not included income inequality variables, therefore, this contributes to the body of literature.

As such, the following research questions: (1) How does intellectual capital and technology affects objective career success? (2) Does income inequality alleviate or abate the relationship between intellectual capital, career success, and information and communications technology? To answer these questions, this paper considers the aforementioned variables of six countries with a high human development index between 1997 and 2018.

The rest of this study is structured as follows, Section 2 details the review of the past literature, Section 3 describes the method and data analysis, Section 4 entails results and discussion, and Section 5 presents the conclusion, and practical and theoretical implications of the study.

2. Literature Review

Intellectual Capital, Technology, and Career Success

Modern processes of economic systems' transformation in the direction of the "knowledge economy" (the new digital economy) stimulate an increasing understanding of the importance of intellectual capital, which increases both the potential for technological development of the economy and the potential for personal growth and career success. The intellectual factor's growing importance contributed to the gradual implantation of the intellectual capital parameters into the sphere of its influence on the effectiveness of managing innovative economic and personal career development studies. Given the diversity of research problems, their relationship with various aspects of the functioning of the economic system at the micro and macro levels, as well as career management, it should be noted that certain aspects of this topic were studied both within the framework of conceptual approaches to disclosing the role of human capital and from the perspective of the intellectual capital concept.

In the previous authors' works, an original comprehensive approach to modeling the processes of accumulation and productive use of human capital in the interests of the development of the economy and the individual has been proposed (Lazareva et al. 2018). When implementing this approach: the methodology for the formation of management strategies that ensure the balance of interests of economic entities in the processes of human resources' reproduction has been substantiated (Lazareva et al. 2020a); economic–mathematical models based on the specification of latent interactions between the level of human capital accumulation and the rate of subjects' development have been proposed (Lazareva et al. 2020b); and factors—characteristics of human capital that determine the level of innovative activity of economic entities—have been revealed and ranked by econometric methods (Anopchenko et al. 2015).

Novation of the authors' approach is based on the methodological foundations of the heuristic need to integrate the four-sector model of human capital as a social resource component of innovative development of the economy into the management system. Components (sectors) of the model proposed by the authors characterize the quality of the individual human capital, the standard of living, the quality of the social sphere, and the environment. Previous studies from the perspective of the intellectual capital concept have addressed the importance of intellectual capital on constructs such as entrepreneurship (Crupi et al. 2020), organizational behavior outcome variables (Hasan 2021), organizational performance (Sutrisno 2021), and environmental performance (Mansoor et al. 2021).

Different studies explore a variety number of factors affecting career success. Some studies consider such objective and subjective aspects of career success as Human Resource Management (HRM) practices (compensation, performance appraisal, training, and development) and personal career motivation (Dabić et al. 2020). Other researchers describe the relationship between human capital development practices and subjective career success and conclude that the main factor in the relationship between development practices and the salary level is the level of the country's development (Bagdadli et al. 2021). Furthermore, it is noteworthy to mention the research about career adaptability and career success in the conditions of a broader career resources framework which showed that career adaptability resources are strongly correlated with other types of career resources, but different facets of career success are conditioned by career adaptability (Haenggli and Hirschi 2020). Analysis of factors influencing objective and subjective career success shows the impact of individual competencies on objective career success, while personal networks were more important for subjective career trajectories Haenggli and Hirschi 2020).

Researchers from Slovakia consider human capital as an obtainable competitive advantage in HRM (Hitka et al. 2019). The study confirmed the hypothesis that the higher the education level of employees, the higher their career expectations and requirements. The link between socially responsible HRM and intellectual capital is also analyzed in the research of scientists from Spain (Barrena-Martinez et al. 2019). Some studies mention gender inequality and imbalance in the development of the careers of men and women in some regions and some jobs (Silva et al. 2021) and other gender patterns of professional success and satisfaction in career development (Sanchez-García and Suárez-Ortega 2021). Another study considers typology and analysis of gender and career success considering an unequal attributes framework (Frear et al. 2019).

A lot of studies consider personal qualities in career success, for example, the importance of the emotional intelligence ability of workers (Sanchez-Gomez et al. 2021), emotion recognition ability (Kranefeld and Blickle 2021), or the role of hardiness and psychological capital (Pordelan and Hosseinian 2021). Other authors consider organizational support as an antecedent for career success, which can manifest itself in organizational culture (Ichim 2020; Lasisi et al. 2019, 2020), and the competitive psychological climate in an organization (Spurk et al. 2021). The importance of intellectual capital in the formation of added value has grown significantly due to the transformation of the manufacturing economy into the knowledge economy (Salvi et al. 2020). There are also more global factors such as the sustainable impact of sociocultural norms, state support programs at the federal and regional levels, as well as digitalization on career satisfaction of employees at different positions (Huđek et al. 2021).

Another field of study is considering the career development trends in self-employment and career success (Koch et al. 2021). The role of intellectual capital is the focus of a lot of studies. Some of them see intellectual capital as a key factor for technological sustainable development (Secundo et al. 2020). Another study considers how intellectual capital provides strong relationships between organizational capabilities and productivity (Huang and Huang and Huang 2020). Intellectual capital is a backbone resource for an organization that stimulates the growth of market value and strengthens sustainable competitive advantages (Gross-Gołacka et al. 2020). Strong interrelationships among intellectual capital, knowledge management infrastructure, knowledge management process, and organizational performance form a system of interaction in the context of career success (Abualoush et al. 2018).

A study analyzed the relationship between organizational trust and intellectual capital and its impact on achieving the requirements and strategic directions of the company's development, based on collected data from open sources, as well as using a questionnaire for a sample of 64 managers of the Korek telecommunications company (Hasan 2021). It is also should be mentioned that in India positive trend coefficients were found in most of the sectors of the economy analyzed in the research on the status and trend of intellectual capital (Sharma and Dharni 2017). The results of the study prove the fact that intellectual capital has a steady upward trend due to the increase in the size of the organization. The role of e-HRM and Performance Pay in understanding the relationship between intellectual capital and organizational performance is also an object of some studies (Lazazzara et al. 2020). Several studies have argued that intellectual capital is the main driver of economic production and a key aspect of sustainable and inclusive socioeconomic development (Suciu and Năsulea 2019; Matos and Vairinhos 2017). In the context of achieving sustainable development goals, information and communication technologies (ICTs) play a significant role as an element of intellectual capital (Steinfield et al. 2010; Allameh 2018).

Some studies analyze the effect of technology on career success considering the demographic predictors of career success and proposing that technological development is critical in removing barriers for different demographic groups that have historically faced them (Fadil et al. 2009). For instance, (Roztocki et al. 2019) describe a conceptual framework that takes into account the four factors—policy, business, technology, and society—that have an effect on socioeconomic development. They argued that technology transforms how organizations run, which has a significant impact on commercial base and business operations, which consequently affects the objective career success of their employees. Furthermore, a study by (Chatterjee 2020) demonstrated that ICT applications such as the Internet and mobile phone along with financial inclusion can increase the growth per capita, which was corroborated by (Aghion et al. 2019). Furthermore, (Baranik et al. 2021) found that with increased use of the Internet, there was an increase in income level. This indicates that with ICT, individuals can achieve high skill levels through knowledge that is accessible via the Internet. Furthermore, individual decisions and choices (e.g., career choice, salary, improved education, etc.) are influenced by the help of ICT (Pico-Saltos et al. 2023).

According to (Kocsis and Xiong 2022), income inequality is a multifaceted topic with important measurements, definitions, and factors, which is commonly measured by income in a region that goes to the top 0.1% or top 1.0% of earners. The Gini index of income inequality is a widely used indicator of income inequality. The Gini index ranges from 0 (i.e., 0%) to 1 (i.e., 100%), with a value of 0 denoting perfect equality and 1 denoting perfect inequality (Kocsis and Xiong 2022). Income inequality has been found to have a negative economic, social, and psychological impact. For instance, opportunity disparity is influenced by income inequality in two different ways. According to studies, when looking at investments in human capital from a static perspective, the returns are not the same for individuals with varied beginning wages. These discrepancies result from an income disparity between the poor and the wealthy, which might widen over time (Adermon et al. 2016). From a dynamic viewpoint, this income disparity might then last for several centuries. Less educated parents typically have lower earnings in countries with more income inequality and typically lack the resources (e.g., finance, technology, etc.) to make investments as freely and readily in their children's human capital (Hu 2021). Due to environmental influences throughout childhood, the offspring of these families also frequently have poorer endowments (Hyytinen et al. 2019). It is inevitably "significantly more difficult for hardworking and talented individuals to earn the benefits they due" as a result of rising income inequality in societies (Yu and Xu 2022). Rather than reflecting individual decisions on the investment of human capital, occupational outcomes increasingly depend on past and current inequities (Coen-Pirani 2015). Managers are then more inclined to associate socially disadvantaged people with more undesirable characteristics, such as lower competence and cognitive skills (Demirtaş-Madran 2020). As a result, research has shown that people from lower socioeconomic backgrounds often face challenges in reaching objective career success in organizations even though they may have valuable intellectual capital (Pitesa and Pillutla 2019). Therefore, as discussed above and depicted in Figure 1, we posit:

Hypothesis 1. *Career success is a function of technology and intellectual capital.*

Hypothesis 2. *Income inequality moderates the relationship between (a) intellectual capital and career success and (b) technology and career success.*

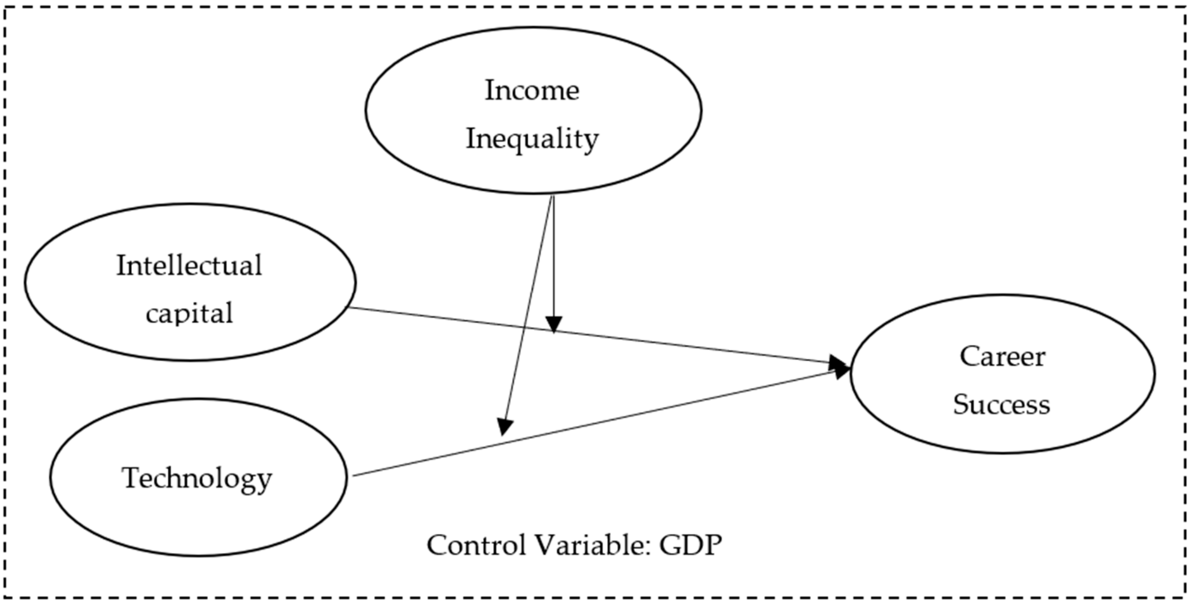

Figure 1. Research Model.

3. Materials and Methods

3.1. Data

Based on the United Nations Development Programme (UNDP)'s human development index (HDI) ranking, this study used panel data from six countries (Norway, Iceland, Germany, Sweden, Denmark, and the Netherlands) with high HDI from 1997 to 2018. Data used were sourced from the World Bank Development Indicator. Panel data were used for the purpose of controlling heterogeneity differences that could arise from the different characteristics that are exhibited by the sample countries. Furthermore, panel data were used because such data have less collinearity, have an extra degree of freedom, and estimates have more variability, and efficiency, and are more informative (Werts et al. 1971). The variables under consideration are career success, intellectual capital, income inequality, and technology. GDP, GDP per person employed GDPPE, Research and Development (RD), income inequality (GINI), and individuals using the Internet (INT) were used as proxies.

Table 1 below gives a description of the variables used as well as their symbols, source, and descriptive statistics. To reduce non-normality and heteroscedasticity, GDP and GDPPE were expressed in logarithm form.

Table 1. Data description and statistics.

Variable	Description	Source
GDPPE	GDP per person employed (constant 2017 PPP USD)	WDI
INT	Individuals using the Internet (% of population)	WDI
RD	Research and development expenditure (% of GDP)	WDI
GDP	GDP (constant 2010 USD)[1]	WDI
GINI	Income inequality (Top 10% share)	WID
GIRD	Interaction of GINI and RD	Authors' computation
GINT	Interaction of GINI and INT	Authors' computation
No. of observations: 132; time span: 1997–2018		

Note: LGDPPE and LGDP are the logarithms of GDPPE and GDP while WDI is the World Development Indicator of the World Bank, WID is World Inequality Database. GDP constant 2010 USD is used for the real GDP variable which is calculated with a fixed or constant price to eliminate the price effect or inflation. Thus, in this study, we obtained GDP constant 2010 USD from World Bank (World Bank 2010) database.

3.2. Model Specification

Several studies have been carried out to determine the antecedents of career success and factors such as social capital, human capital, and career capital competence were revealed (Guo et al. 2012; Valk et al. 2014); however, these studies have carried out the study using primary data and have not considered this at a national level. (Shockley et al. 2016) considered salary as an objective indicator of career success; therefore, this current study uses GDP per person employed as a proxy for career success. Furthermore, several studies (such as (Cristea et al. 2020)) have used research and development expenditure as indicators of national intellectual capital. Similarly, studies (such as (Azam et al. 2021; Razzaq et al. 2021)) have used "individuals using the Internet" as an indicator for information and communication technology. Furthermore, several studies (Asongu and Odhiambo 2019; Behringer and van Treeck 2018; Masud et al. 2018) have used the Atkinson index and Gini coefficient as an indicator for income inequality; therefore, this study used the GINI coefficient as a proxy for income inequality such that:

$$GDPPE = f(RD,\ INT,\ GDP,\ GINI) \tag{1}$$

$$GDPPE = F(INT,\ GDP,\ GIRD) \tag{2}$$

$$GDPPE = f(RD,\ GDP,\ GINT) \tag{3}$$

$$lnGDPPE_{i,t} = \propto + \beta_1 RD_{i,t} + \beta_2 INT_{i,t} + \beta_3 lnGDP_{i,t} + \beta_4 GINI_{i,t} + \beta_5 GIRD_{i,t} + \beta_6 GINT_{i,t} + \varepsilon_{i,t} \tag{4}$$

3.3. Methodology

3.3.1. Unit Root Tests

One of the most common tests in the economic field is the panel unit root test, and this is because of its higher power than that of the unit toot test, which tests for individual time series. Panel unit root tests were used to identify the order of each variable's integration. For spurious regression to be avoided, the Augmented (Dickey and Fuller 1981) and the Phillips and Perron (1988) tests were carried out. Successively, Pedroni's (1999) and Kao's (1999) and cointegration tests were used to establish the long-term relationships among the variables. The Pedroni (1999) cointegration test equation is stated below:

$$X_{it} = \varphi_{it}\lambda_i + \partial_i + \vartheta_i + \mu_{it} \tag{5}$$

To ascertain if there is cointegration from the static long-run regression form, an econometric test on the residual needs to be carried out, and the equation is stated below:

$$\mu_{it} = \mathbb{P}\mu_{it-1} + y_{it} \tag{6}$$

The null hypothesis states that there is no cointegration between the variables and is considered as pi = 1.

3.3.2. PMG-ARDL (Pooled Mean Group Autoregressive Distributive Lag Model)

The PMG-ARDL was used in this study to examine the long-run equilibrium relationships between intellectual capital, career success, technology, and income inequality in six countries with high HDI. The PMG-ARDL is considered to be effective because it uses the cointegration form of the ordinary (standard) ARDL model that (Pesaran et al. 1999) developed. Furthermore, the information criteria feature, which is enhanced, uses automatic lag selection and has the capacity to reveal the short- and long-run models. The PMG-ARDL is represented with Equation (7) below:

$$\Delta lny_{i,t} = \varphi_i ECT_{i,t} + \sum_{j=0}^{q-1} \Delta lnX_{i,t-j}\beta_{i,j} + \sum_{j-1}^{p-1} \psi_{i,j}\Delta lny_{i,t-j} + \varepsilon_{i,t} \tag{7}$$

where y denotes the dependent variable (GDPPE), X denotes the regressors (INT, RD, GINI, GDP, GIRD, and GINT) with the same number of lags across individual cross-sectional units i in the time t, φ symbolizes the adjustment coefficient, ε signifies the error term θ represents the long-run coefficient that produces β and ψ estimates after reaching convergence, and Δ denotes the difference operator.

3.3.3. Robustness Test

To ascertain the significance and robustness of the empirical estimation of the PMG-ARDL, the study used the Pairwise Dumitrescu Hurlin causality test (Dumitrescu and Hurlin 2012) which allows a heterogeneous panel setting the Granger non-causality within the independent and dependent variables. Due to the fact that the T dimension (22) is greater than the N dimension (6), the asymptotic distribution was used. Additionally, the model is established on the Vector Autoregressive Model (VAR) and is also deemed suitable for a balanced and heterogeneous pane. The linear model representation is stated in the equation below:

$$M_{i,t} = \sum_{\mathcal{V}-1}^{V} \mathbb{Z}_i^{(k)} M_{i,t-1} + \sum_{\mathcal{V}-1}^{V} \Upsilon_i^{(k)} \S_{i,t-v} + \epsilon_{i,t} \tag{8}$$

where M and Υ represent the sampled five variables' pair match, k denotes the lag length, $\mathbb{Z}_i^{(k)}$ is the autoregressive component parameter, $\Upsilon_i^{(k)}$ symbolizes the coefficient of regression which is acceptable to vary within the groups while $\epsilon_{i,t}$ is the error term. The test of causality allows for heterogeneity.

4. Results

The synopsis of the descriptive statistics is stated in Table 2. It is expedient to establish the fundamental dispersion and central tendency of the variables as well as how they performed over the period under investigation (1997–2018). Table 2 indicates that GDP per person employed has a minimum of USD 11.097 and a maximum (highest) of USD 11.76 while the minimum and maximum percentages of the population using the Internet are 6.71 and 99.01, respectively. All variables being considered are negatively skewed except for GINI as well as research and development. A sample size panel of 132 observations was used in this study with all series not normally distributed, except for GDP per employment which is normally distributed; given this, the null hypothesis of normality is rejected.

Table 2. Descriptive statistics.

	LGDPPE	INT	RD	GINI	LGDP	GIRD	GINT
Mean	11.502	74.666	2.423	0.313	26.614	0.764	23.477
Median	11.521	84.925	2.408	0.309	26.804	0.719	26.645
Maximum	11.760	99.011	3.908	0.383	28.998	1.173	33.464
Minimum	11.097	6.711	1.456	0.268	22.922	0.452	2.105
Std. Dev.	0.137	24.875	0.631	0.026	1.679	0.224	8.119
Skewness	−0.653	−1.191	0.304	0.969	−0.889	0.263	−1.077
Kurtosis	3.687	3.146	1.953	3.620	3.156	1.606	2.966

No. of observations: 132. Note: LGDPPE and LGDP are the logarithms of GDPPE and GDP while WDI is the World Development Indicator of the World Bank.

Furthermore, a correlation matrix analysis was conducted to investigate the relationship between the variables which is shown in Table 3 below. It was observed that the relationship between GDPPE and individuals using the Internet, income inequality, GDP, and GINT are positively significant but inversely significant with research and development. With respect to individuals using the Internet, there is a positive and significant relationship with research and development. Income inequality. GIRD and GINT but an inverse but significant relationship with GDP. In the case of research and development, there is a positive and significant relationship with other variables except for GDP where the relationship is not statistically significant while income inequality has a positive and significant while income inequality has a positive and significant relationship with all variables. GDP is positively related to GIRD and GINT but the relationship is significant for GIRD but not for GINT while the relationship between GIRD and GINT is positive and significant.

Table 3. Correlation matrix.

Variable	LGDPPE	INT	RD	GINI	LGDP	GIRD	GINT
LGDPPE	1.00						
INT	0.42 ***	1.00					
RD	−0.29 ***	0.15 ***	1.00				
GINI	0.19 ***	0.13 *	0.28 ***	1.00			
LGDP	0.55 ***	−0.11	0.05	0.42 ***	1.00		
GIRD	−0.20 ***	0.16 **	0.96 ***	0.54 ***	0.18 **	1.00	
GINT	0.45 ***	0.97 ***	0.20 ***	0.37 ***	0.01	0.28 ***	1.00

***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

In econometrics analysis, it is pertinent to carry out a stationarity test to avoid spurious regression. Table 4 displays the result of the ADF-Fisher and PP-Fisher unit root analysis. It was observed that all variables were stationary and significant at 1%; therefore, since the entire series became stationary at the first difference, we proceed to the cointegration of the data. Based on Fisher's (trace and max-Eigen) and Kao residual cointegration test as shown in Table 5, the null hypothesis was rejected since the probability for Fisher's max-eigen and trace probability was significant. Therefore, the results that the variables are cointegrated are accepted and we proceeded to examine the degree of cointegration by using the PMG-ARDL as shown in Table 6.

Table 4. Unit root.

Variable	ADF-Fisher			PP-Fisher	
	Model	**Levels**	**First Difference**	**Levels**	**First Difference**
LGDPPE	Constant	11.19	51.67 ***	13.52	75.50 ***
	Trend	17.39	36.85 ***	14.77	64.29 ***
	None	0.19	64.05 ***	0.06	63.28 ***
RD	Constant	6.30	50.18 ***	6.68	54.60 ***
	Trend	16.54 *	34.37 ***	10.04	41.81 ***
	None	1.99	71.11 ***	2.00	78.16 ***
INT	Constant	323.96 ***	45.34 ***	168.30 ***	33.57 ***
	Trend	6.99	65.03 ***	13.33	56.66 ***
	None	2.88	44.61 ***	0.88	47.55 ***
GINI	Constant	14.71	87.06 ***	13.86	92.67 ***
	Trend	11.45	67.23 ***	11.46	85.92 ***
	None	3.92	122.55 ***	3.45	125.36 ***
LGDP	Constant	7.89	46.73 ***	9.86	60.20 ***
	Trend	18.02 *	28.59 ***	11.68	48.78 ***
	None	0.06	46.83 ***	0.00	45.19 ***
GIRD	Constant	3.16	74.37 ***	4.16	75.71 ***
	Trend	17.13 *	55.06 ***	10.15	61.02 ***
	None	2.57	91.37 ***	2.48	90.06 ***
GINT	Constant	58.77 ***	38.66 ***	65.41 ***	45.17 ***
	Trend	10.65	67.95 ***	4.67	67.90 ***
	None	1.54	52.29 ***	0.91	57.80 ***

Note: *** and * indicate 1% and 10% levels of significance, respectively.

Table 5. Cointegration result.

Cointegration Statistics	Value
1. Kao cointegration test	−3.50 ***
2. Fisher cointegration (Trace Test)	
None	8.32
At most 1	93.49 ***
At most 2	249.70 ***
At most 3	124.10 ***
Fisher cointegration (max-eigen test)	
None	8.32
At most 1	93.49 ***
At most 2	165.60 ***
At most 3	67.30 ***

*** represent significance levels at 1%.

Table 6. Pooled mean group with dynamic autoregressive distributed lag [PMG-ARDL (1, 1, 1, 1, 1)].

Variable	Model 1	Model 2	Model 3
Long run			
INT	0.0041 (0.0009) ***	0.0018 (0.002) ***	-
RD	0.1255 (0.0422) ***	-	0.1087 (0.0423) ***
LGDP	−0.3428 (0.2188) *	0.3252 (0.0398) ***	−0.2098 (0.2185)
GIRD	-	−0.0181 (0.0321)	-
GINT	-	-	0.0108 (0.0028) ***
Short run			
ECT (−1)	−0.1329 (0.0719) *	−0.3034 (0.0897) ***	−0.1328 (0.0795) *
INT	0.0001 (0.0001)	0.0001 (0.0002)	-
RD	−0.0287 (0.0035) ***	-	−0.0251 (0.0057) ***
LGDP	0.6848 (0.0915) ***	0.6125 (0.077) ***	0.6479 (0.0837) ***
GIRD	-	−0.0524 (0.0262) **	-
GINT	-	-	3.10×10^{-5} (0.0004)
Constant	2.6891 (1.4679) *	0.8437 (0.2332) ***	2.2192 (1.3411) *

Table 6. *Cont.*

Variable	Model 1	Model 2	Model 3
Norway			
ECT (−1)	−0.2626 (0.0041) ***	−0.2492 (0.0087) ***	−0.2350 (0.0068) ***
INT	0.0002 (1.38 × 10^{-7}) ***	0.0008 (2.13 × 10^{-7}) ***	-
RD	−0.0138 (0.0005) ***	-	0.0019 (0.0008) *
LGDP	0.9113 (0.0241) ***	0.7746 (0.0341) ***	0.8450 (0.0412) ***
GIRD	-	−0.0564 (0.0083) ***	-
GINT	-	-	0.0004 (1.64 × 10^{-6}) ***
Constant	5.325799 **	0.6998 (0.1299) ***	3.9490 (2.2275)
Iceland			
ECT (−1)	−0.0452 (0.0009)	−0.3365 (0.0161) ***	−0.0628 (0.0011) ***
INT	2.06 × 10^{-5} (3.17 × 10^{-7}) ***	−0.0002 (2.8× 10^{-7}) ***	-
RD	−0.0249 (0.0002) ***	-	−0.0278 (0.0002) ***
LGDP	0.4838 (0.0066) ***	0.3363 (0.0113) ***	0.4612 (0.0064) ***
GIRD	-	−0.0809 (0.0013) ***	-
GINT	-	-	−0.0010 (1.47× 10^{-7}6) ***
Constant	0.8451 (0.2902) **	1.2091 (0.2855) **	0.9864 (0.1966) **
Germany			
ECT (−1)	−0.0054 (0.0006) ***	0.0025 (0.0029)	0.0163 (0.0006) ***
INT	0.0006 (1.56E−07) ***	0.0005 (1.5 × 10^{-7}) ***	-
RD	−0.0296 (0.0009) ***	-	−0.0290 (0.0009) ***
LGDP	0.8019 (0.0006) ***	0.7717 (0.0058) ***	0.7921 (0.0068) ***
GIRD	-	−0.1632 (0.0069) ***	-
GINT	-	-	0.0005 (1.6 × 10^{-6}) ***
Constant	0.1061 (0.2789)	−0.0075 (0.0119)	−0.2812 (0.1630)
Sweden			
ECT (−1)	−0.0590 (0.0008) ***	−0.5232 (0.0068) ***	−0.0433 (0.0008) ***
INT	−0.0002 (1.61× 10^{-7}) ***	−0.0009 (7.88 × 10^{-8}) ***	-
RD	−0.0316 (0.0001) ***	-	−0.0346 (9.71 × 10^{-5}) ***
LGDP	0.7311 (0.0042) ***	0.5584 (0.0042) ***	0.7120 (0.0046) ***
GIRD	-	0.0038 (0.006) ***	-
GINT	-	-	0.0005 (1.21 × 10^{-6}) ***
Constant	1.1712 (0.2249) ***	1.3519 (0.2107) ***	0.7082 (0.1662)
Denmark			
ECT (−1)	0.0065 (0.0022) **	−0.1451 (0.0066) ***	0.0121 (0.0032) **
INT	0.0002 (1.31 × 10^{-7}) ***	−0.0002 (1.38× 10^{-7}) ***	-
RD	−0.0394 (0.0007) ***	-	−0.0371 (0.0008) ***
LGDP	0.3398 (0.0264) ***	0.4652 (0.0103) ***	0.3294 (0.0215) ***
GIRD	-	0.0071 (0.0067)	-
GINT	-	-	0.0009 (1.35 × 10^{-6}) ***
Constant	−0.1205 (0.8611)	0.4111 (0.0649) ***	−0.1909 (0.8599)
Netherlands			
ECT (−1)	−0.4323 (0.0076) ***	−0.5691 (0.0104) ***	−0.4839 (0.0109) ***
INT	6.00 × 10^{-5} (1.55 × 10^{-7}) ***	0.0007 (1.89 × 10^{-7}) ***	-
RD	−0.0328 (0.0006) ***	-	−0.0238 (0.0007) ***
LGDP	0.8408 (0.0077) ***	0.7688 (0.0118) ***	0.7480 (0.0087) ***
GIRD	-	−0.0249 (0.0067) **	-
GINT	-	-	−0.0013 (1.86 × 10^{-6}) ***
Constant	8.8066 (2.2557) **	1.3978 (0.3558) **	8.1438 (3.3421)

Note: The numbers in parentheses are the standard errors, while ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

Figure 2 depicts the confidence ellipse diagnostic test and is portrayed by the stability points centralized within the ellipse. The figure suggests that the estimation model has a significant confidence level.

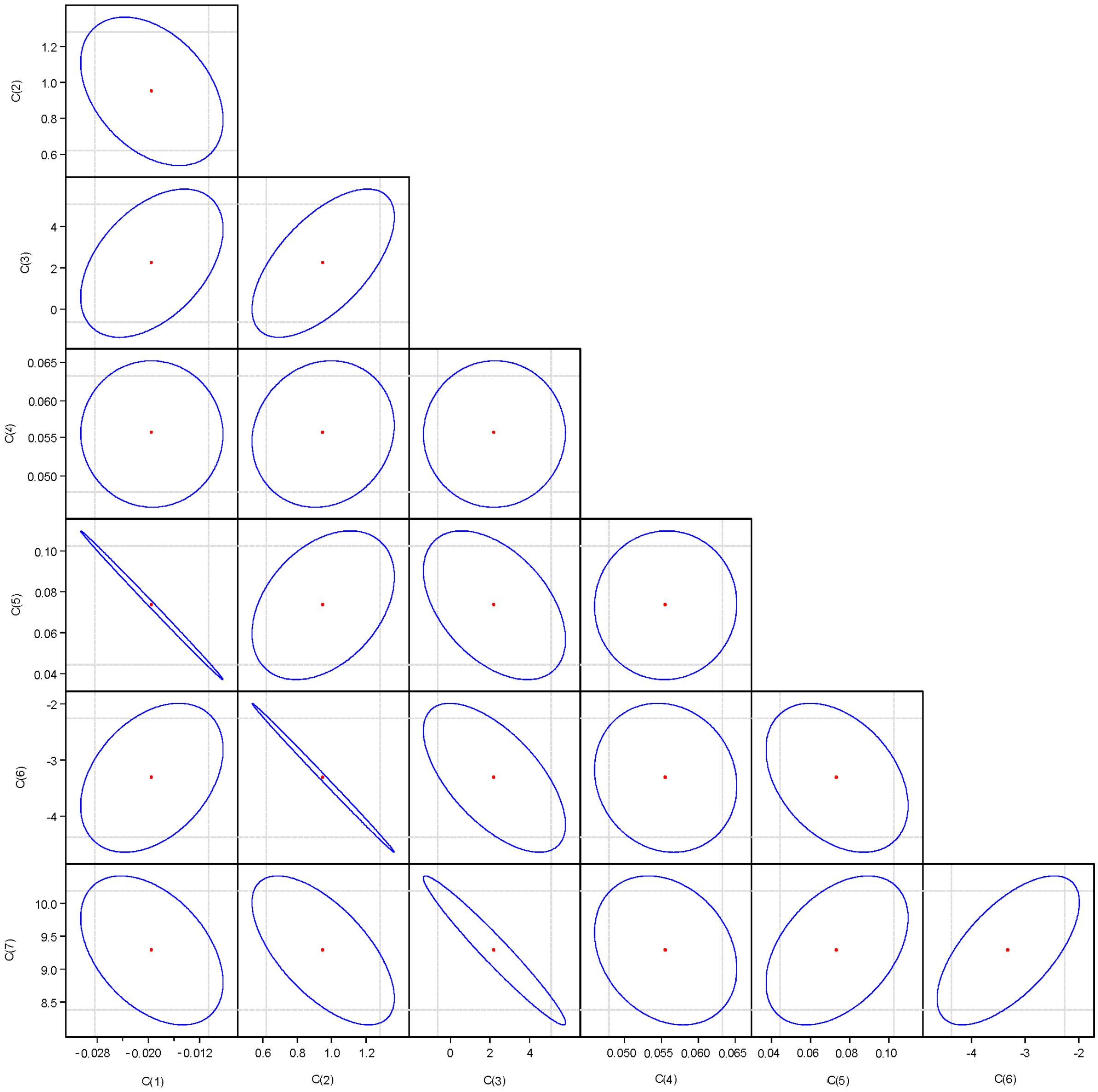

Figure 2. Confidence ellipse.

5. Discussion

Investigation from the PMG-ARDL shows that there is a positive and significant relationship between technology and career success in the long run as a 1% increase in INT leads to a 0.0041% increase in GDPPE. However in model 2, where income inequality moderates the relationship, there is a decrease in the percentage of GDPPE. Furthermore, there is also a positive and significant relationship between RD and GDPPE, as a 1% increase in RD leads to a 0.13% increase in GDPPE. Furthermore, as income inequality was introduced as a moderator, there was a decline to 0.11%. Contrariwise, there is an inverse and significant relationship between GDP and GDPPE in model 1, while a positive and significant relationship in model 2, but an insignificant and inverse relationship in model 3. This indicates that income inequality increases economic growth in the observed countries in the long run, which could be that the few wealthy individuals influence economic growth (Bilan et al. 2020; Shen and Zhao 2022) through an increase in infrastructure, an increase in the level of investment, etc. Likewise, in model two, the interaction of income inequality and RD leads to a decrease in GDPPE as a 1% increase in GIRD leads to a 0.018% decline in GDPPE.

The PMG-ARDL model shows that there is a significant and positive association between information and communication technology and career success. In terms of research and development (intellectual capital), there is a positive and linear relationship with GDPPE (career success) in the long term, but a feedback relationship in the short term; this indicates that policymakers should invest in the development and improvement of intellectual capital to ensure objective career success among citizens. We expected (initial hypothesis) that the relationship between income inequality and career success would be inverse. However, research shows that for a family worker, there is a linear and positive relationship with GDP per employee.

Surprisingly, in Iceland, there is an inverse relationship between career success and intellectual capital. In the case of Germany, in the short term, there is a positive and significant linear relationship between people using the Internet and career success, as well as between research and development and career success; however, surprisingly, the relationship between income inequality and career success rates is positive and significant. For Sweden, there was an inverse relationship between people using the Internet and career success, and research and development with career success, as well as a positive and significant linear relationship between income inequality and career success, which were all unforeseen. For Denmark, a 1% increase in the number of people using the Internet, intellectual capital, and income inequality results in −0.0007%, −0.03%, and −0.04%, respectively, for career success, while for the Netherlands there is a positive and significant linear relationship between Internet use and career success, as well as between income inequality and career success, while there is a significant and inverse relationship between intellectual capital and career success. In addition, the impact of Internet use increased research, and development on career success in the group of countries with the highest human development index is statistically positive and significant. Furthermore, inequality was found to significantly moderate the relationship between intellectual capital, technology, and career success.

Finally, Table 7 describes the Dumitrescu and Hurlin panel causality test, which is used to examine the Granger non-causality from independent variable to dependent variable as outlined by (Dumitrescu and Hurlin 2012). Findings from our analysis reveal that there is a one-way causality between information and communications technology and career success which suggests that access and use of the Internet result in career success. The Internet facilitates communication and information sharing which helps in improving employability, career competencies, and also for career interventions (Wang 2013). A study conducted by (Dan et al. 2018) revealed that access to information is structural empowerment that encourages innovative behavior which affects career success. Similarly, (Green et al. 2011) carried out research for the Institute for Employment Research and affirm that access to and use of the Internet plays an important role in information and knowledge exploration and transfer which was also affirmed by a study carried out by (Cillo et al. 2019).

Research and development cause GDP per person employed which means that intellectual capital leads to career success which is in congruence with findings from (Muwardi et al. 2020) research. A study conducted by (Freimane and Bāliņa 2016) over 14 year period (2000 to 2013) to examine the role of research and development on gross domestic product per person employed in EU member states and resolved that the impact is significant and positive which was also affirmed in the (Kose et al. 2020) study on sustainable research and development-led growth in EU.

We expected that objective career success will lead to economic growth, as this has been established in different studies such as (Barin et al. 2020; Simonova et al. 2015). Our finding shows one-way causality between economic development and objective career success which has been established by (Naseer et al. 2015). Their study established that when employees have objective career success, this improves organizational performance and invariably bolsters economic growth. Furthermore, according to a report by (Georgescu and Herman 2019), sustainable and inclusive economic growth creates decent jobs and increases labor productivity.

Table 7. Dumitrescu and Hurlin's (2012) Granger causality.

Null Hypothesis	z-Bar	Causality
INT does not homogeneously cause LGDPPE	2.0005 ***	INT→LGDPPE
LGDPPE does not homogeneously cause INT	−1.2142	No causality
RD does not homogeneously cause LGDPPE	1.4220 *	RD→LGDPPE
LGDPPE does not homogeneously cause RD	2.1847 ***	LGDPPE→RD
GINI does not homogeneously cause LGDPPE	1.0457	No causality
LGDPPE does not homogeneously cause GINI	1.5902	No causality
LGDP does not homogeneously cause LGDPPE	−0.0803 **	No causality
LGDPPE does not homogeneously cause LGDP	1.9577	LGDPPE→LGDP
GINT does not homogeneously cause LGDPPE	2.1451 **	GINT→LGDPPE
LGDPPE does not homogeneously cause GINT	−0.9602	No causality
GIRD does not homogeneously cause LGDPPE	2.1505 **	GIRD→LGDPPE
LGDPPE does not homogeneously cause GIRD	3.4594 ***	LGDPPE→GIRD
RD does not homogeneously cause INT	0.0615	No causality
INT does not homogeneously cause RD	2.4889 ***	INT→RD
GINI does not homogeneously cause INT	0.0894	No causality
INT does not homogeneously cause GINI	1.9911 **	INT→GINI
LGDP does not homogeneously cause INT	−1.4352	No causality
INT does not homogeneously cause LGDP	−1.3883	No causality
GINT does not homogeneously cause INT	−0.5240	No causality
INT does not homogeneously cause GINT	0.6621	No causality
GIRD does not homogeneously cause INT	−0.6364	No causality
INT does not homogeneously cause GIRD	2.6100 ***	INT→GIRD
GINI does not homogeneously cause RD	1.5091	No causality
RD does not homogeneously cause GINI	−0.2729	No causality
LGDP does not homogeneously cause RD	4.8199 ***	LGDP→RD
RD does not homogeneously cause LGDP	0.2571	No causality
GINT does not homogeneously cause RD	2.0753 **	GINT→RD
RD does not homogeneously cause GINT	0.3350	No causality
GIRD does not homogeneously cause RD	1.5869	No causality
RD does not homogeneously cause GIRD	0.3932	No causality
LGDP does not homogeneously cause GINI	0.2211	No causality
GINI does not homogeneously cause LGDP	0.4524	No causality
GINT does not homogeneously cause GINI	2.0475 **	GINT→GINI
GINI does not homogeneously cause GINT	0.8354	No causality
GIRD does not homogeneously cause GINI	−0.1849	No causality
GINI does not homogeneously cause GIRD	0.5700	No causality
GINT does not homogeneously cause LGDP	−1.0167	No causality
LGDP does not homogeneously cause GINT	−1.1206	No causality
GIRD does not homogeneously cause LGDP	1.7381 **	GIRD→LGDP
LGDP does not homogeneously cause GIRD	3.7540 ***	LGDP→GIRD
GIRD does not homogeneously cause GINT	−0.6968	No causality
GINT does not homogeneously cause GIRD	2.5586 ***	GINT→GIRD

Note: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

Furthermore, information and communications technology have a one-way causality to research and development, income inequality, and interaction variable between income inequality and research and development. There is a bi-directional causality running from the interaction variable (GIRD) and career success as well as between the interaction variable (GIRD) and economic growth. There is a one-way causality running from the interaction variable (GINT) and career success, intellectual capital, income inequality, and GIRD.

6. Conclusions and Policy Matters

This current study examines the relationship between intellectual capital and career success as well as the technology–career success nexus. Adding to this novelty, the study considered income inequality as a moderator. The current study pioneered a PMG-ARDL regression model (a modification of a vector autoregression (VAR) model) to assess the long-term equilibrium relationships between intellectual capital, career success, technology, and income inequality in six countries with a high human development index (HDI). Panel data from six countries—Norway, Iceland, Germany, Sweden, Denmark, and the Netherlands—for the updated period (1997–2018) served as the information base for the implementation of this approach. As variables of the model, indicators of intellectual capital and career success, as well as variables/proxies of both technologies and income inequality, the World Bank data were used, characterizing, respectively, expenditures on research and development (% of GDP) (RD), GDP per person employed (GDPPE), individuals using the Internet (% of the population) (INT) and income inequality total (top 10% share) (GINI).

Education is a key factor for both intellectual capital and research and development. This result shows that career success depends on the implementation of targeted educational policy mechanisms, the expansion of research and development, as well as on the expansion of communication via the Internet. The results of our analysis show that there is a one-way causal relationship between information and communication technology and career success, which suggests that access and use of the Internet lead to career success. However, our conclusion shows a one-sided causal relationship between economic development and objective career success. In addition, sustainable and inclusive economic growth creates decent jobs and increases productivity.

Another important part of this research is its relevance to policy through the tools of government, public–private partnerships, and other affiliated institutions. Using the results of the constructed model and the analysis of specific factors of the country, it can be recommended to focus on the political mechanisms in the implementation of targeted strategies and tools of educational policy, the expansion of research and development, as well as the expansion of communications via the Internet. Investments in the development and improvement of intellectual capital will lead to objective career success among citizens. Education is a key factor for both intellectual capital and research and development. Achieving career success is associated with the development of intellectual capital and as a result, economic growth.

To achieve SDG 8, this study provides the following practical implications: (1) governments and stakeholders should promote development-oriented policies that encourage decent job creation as well as equal pay for work of equal value to reduce income inequality; (2) create policies to reduce the proportion of youth not in education, employment, and training because our study has highlighted that education is an important factor in acquiring intellectual capital; (3) more sensitization in the productive use of the Internet should be conducted bringing new capacities, knowledge acquisition, and transfer not only for intellectual capital but also for business operations which will have a snowball effect on organizational profit and employee income.

Limitations and Future Research

Just as in any case of a research article, this study is not without limitations. Firstly, the study set out to consider the top ten countries with the highest human development index rank, but due to the unavailability of data for all variables of interest, the top six countries were considered. Future studies should carry out a comparative study based on very high, high, middle, and low human development index rankings. Secondly, other variables such as gender, education, health, and uncertainty can be considered moderating variables. Thirdly, the study is limited in scope covering data span from 1997 to 2018, future studies can benefit from this limitation by re-validating the outcomes of the current study with more recent data. Lastly, the countries under consideration have low-income inequality, future studies can take countries with high-income inequality into consideration. Other studies could replicate the study by carrying out a cross-country or income-group study to have a better understanding of the research domain.

Author Contributions: Conceptualization, T.T.L.; methodology, T.T.L.; formal analysis, T.T.L.; investigation, G.A.A. and A.D.M.; resources, A.D.M.; data curation, T.T.L.; writing—original draft preparation, T.T.L., G.A.A., J.V.G. and E.I.L.; writing—review & editing, T.T.L.; supervision, E.I.L. and A.D.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethical review and approval were waived for this study, given that the data analysed are open sourced.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available on request.

Conflicts of Interest: The authors declare no conflict of interest.

Note

1 https://databank.worldbank.org/metadataglossary/jobs/series/NY.GDP.PCAP.KD (accessed on 10 January 2023).

References

Abualoush, Shadi, Ra'ed Masa'deh, Khaled Bataineh, and Ala'aldin Alrowwad. 2018. The Role of Knowledge Management Process and Intellectual Capital as Intermediary Variables between Knowledge Management Infrastructure and Organization Performance. *Interdisciplinary Journal of Information, Knowledge, and Management* 13: 279–309. [CrossRef] [PubMed]

Adermon, Adrian, Mikael Lindahl, and Mårten Palme. 2016. Dynastic Human Capital, Inequality and Intergenerational Mobility. *American Economic Review* 11: 1523–48.

Aghion, Philippe, Céline Antonin, and Simon Bunel. 2019. Artificial Intelligence, Growth and Employment: The Role of Policy. *Economie et Statistique* 510: 149–64. [CrossRef]

Ali, Bayad Jamal, and Govand Anwar. 2021. Intellectual Capital: A Modern Model to Measure the Value Creation in a Business. *International journal of Engineering, Business and Management* 5: 31–43. [CrossRef]

Allameh, Sayyed Mohsen. 2018. Antecedents and Consequences of Intellectual Capital. *Journal of Intellectual Capital* 19: 858–74. [CrossRef]

Al-Nashmi, Murad Mohammed, and Redhwan Ali Amer. 2014. The Impact of Information Technology Adoption on Employee Productivity in Nongovernemental Organizations in Yemen. *International Journal of Social Sciences and Humanities Research* 3: 32–50.

Alvino, Federico, Assunta di Vaio, Rohail Hassan, and Rosa Palladino. 2020. Intellectual Capital and Sustainable Development: A Systematic Literature Review. *Journal of Intellectual Capital* 22: 76–94. [CrossRef]

Anopchenko, T., E. Lazareva, I. S. Bagdasaryan, Z. A. Vasileva, and O. A. Almabekova. 2015. Human Resource Innovative Management Using the Tools of Econometrics. Paper presented at the SGEM International Multidisciplinary Scientific Conference on Social Sciences and Arts, Albena, Bulgaria, August 26; (см. в книгах). pp. 393–99.

Arias-Pérez, José, Juan Velez-Ocampo, and Juan Cepeda-Cardona. 2021. Strategic Orientation toward Digitalization to Improve Innovation Capability: Why Knowledge Acquisition and Exploitation through External Embeddedness Matter. *Journal of Knowledge Management* 22: 1319–35. [CrossRef]

Asongu, Simplice A., and Nicholas M. Odhiambo. 2019. How Enhancing Information and Communication Technology Has Affected Inequality in Africa for Sustainable Development: An Empirical Investigation. *Sustainable Development* 27: 647–56. [CrossRef]

Azam, Anam, Muhammad Rafiq, Muhammad Shafique, Haonan Zhang, and Jiahai Yuan. 2021. Analyzing the Effect of Natural Gas, Nuclear Energy and Renewable Energy on GDP and Carbon Emissions: A Multi-Variate Panel Data Analysis. *Energy* 219: 119592. [CrossRef]

Bagdadli, Silvia, Martina Gianecchini, Maike Andresen, Rick Cotton, Robert Kaše, Mila Lazarova, Adam Smale, Janine Bosak, Jon P. Briscoe, Katharina Chudzikowski, and et al. 2021. Human Capital Development Practices and Career Success: The Moderating Role of Country Development and Income Inequality. *Journal of Organizational Behavior* 42: 429–47. [CrossRef]

Baranik, Lisa, Brandon Gorman, and Natalie Wright. 2021. Wasta and Its Relationship to Employment Status and Income in the Arab Middle East. *Current Sociology*, 1–18. [CrossRef]

Barin, Nurgül Emine, Sabriye Kundak, and Vildan Saba Cenikli. 2020. The Effects of Female Employment on Economic Growth: An Application of Panel Data on the Member Countries of the Organisation of Islamic Cooperation. In *Contemporary Issues in Business Economics and Finance*. Bingley: Emerald Publishing Limited Bingley.

Barrena-Martinez, Jesus, Macarena López-Fernández, and Pedro M. Romero-Fernández. 2019. The Link between Socially Responsible Human Resource Management and Intellectual Capital. *Corporate Social Responsibility and Environmental Management* 26: 71–81. [CrossRef]

Behringer, Jan, and Till van Treeck. 2018. Income Distribution and the Current Account. *Journal of International Economics* 114: 238–54. [CrossRef]

Bhatti, Sabeen Hussain, Gabriele Santoro, Aisha Sarwar, and Anna Claudia Pellicelli. 2021. Internal and External Antecedents of Open Innovation Adoption in IT Organisations: Insights from an Emerging Market. *Journal of Knowledge Management* 25: 1726–44. [CrossRef]

Bilan, Yuriy, Halyna Mishchuk, Natalia Samoliuk, and Halyna Yurchyk. 2020. Impact of Income Distribution on Social and Economic Well-Being of the State. *Sustainability* 12: 429. [CrossRef]

Birtchnell, Thomas, Tillmann Böhme, and Robert Gorkin. 2017. 3D Printing and the Third Mission: The University in the Materialization of Intellectual Capital. *Technological Forecasting and Social Change* 123: 240–49. [CrossRef]

Chatterjee, Amrita. 2020. Financial Inclusion, Information and Communication Technology Diffusion, and Economic Growth: A Panel Data Analysis. *Information Technology for Development* 26: 607–35. [CrossRef]

Cillo, Valentina, Alexeis Garcia-Perez, Manlio del Giudice, and Francesca Vicentini. 2019. Blue-Collar Workers, Career Success and Innovation in Manufacturing. *Career Development International* 24: 529–44. [CrossRef]

Cinquini, Lino, Emilio Passetti, Andrea Tenucci, and Marco Frey. 2012. Analyzing Intellectual Capital Information in Sustainability Reports: Some Empirical Evidence. *Journal of Intellectual Capital* 13: 531–61. [CrossRef]

Coen-Pirani, Daniele. 2015. Human Capital Accumulation in a Federation. *European Economic Review* 76: 104–24. [CrossRef]

Cristea, Mirela, Graţiela Georgiana Noja, Nicu Marcu, Marian Siminică, and Diana-Mihaela Ţîrcă. 2020. Modelling EU Bioeconomy Credentials in the Economic Development Framework: The Role of Intellectual Capital. *Technological and Economic Development of Economy* 26: 1139–64. [CrossRef]

Crupi, Antonio, Fabrizio Cesaroni, and Alberto Di Minin. 2020. Understanding the Impact of Intellectual Capital on Entrepreneurship: A Literature Review. *Journal of Intellectual CapitalI* 22: 528–59. [CrossRef]

Dabić, Marina, Božidar Vlačić, Veronica Scuotto, and Merrill Warkentin. 2020. Two Decades of the Journal of Intellectual Capital: A Bibliometric Overview and an Agenda for Future Research. *Journal of Intellectual Capital* 22: 458–77. [CrossRef]

Dan, Xin, Suhuan Xu, Jingying Liu, Ruonan Hou, Yanhui Liu, and Hongwen Ma. 2018. Innovative Behaviour and Career Success: Mediating Roles of Self-Efficacy and Colleague Solidarity of Nurses. *International Journal of Nursing Sciences* 5: 275–80. [CrossRef] [PubMed]

Demirtaş-Madran, H. Andaç. 2020. Exploring the Motivation Behind Discrimination and Stigmatization Related to COVID-19: A Social Psychological Discussion Based on the Main Theoretical Explanations. *Frontrontiers in Psychoogyl* 11: 3204. [CrossRef] [PubMed]

Dickey, David A., and Wayne A. Fuller. 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* 49: 1057–72. [CrossRef]

Dumitrescu, Elena-Ivona, and Christophe Hurlin. 2012. Testing for Granger Non-Causality in Heterogeneous Panels. *Econonomic Modelingl* 29: 1450–60. [CrossRef]

Fadil, Paul, Cindi Smatt, Sharon L. Segrest, and Crystal Owen. 2009. The Moderating Effects of Technology on Career Success: Can Social Networks Shatter the Glass Ceiling? *Journal of International Technology and Information Management* 18: 8. [CrossRef]

Frear, Katherine A., Samantha C. Paustian-Underdahl, Eric D. Heggestad, and Lisa Slattery Walker. 2019. Gender and Career Success: A Typology and Analysis of Dual Paradigms. *Journal of Organizational Behavior* 40: 400–16. [CrossRef]

Freimane, Rita, and Signe Bāliņa. 2016. Research and Development Expenditures and Economic Growth in the EU: A Panel Data Analysis. *Economics and Business* 29: 5–11. [CrossRef]

Georgescu, Maria-Ana, and Emilia Herman. 2019. Productive Employment for Inclusive and Sustainable Development in European Union Countries: A Multivariate Analysis. *Sustainability* 11: 1771. [CrossRef]

Green, Anne E., Maria de Hoyos, Yuxin Li, and David Owen. 2011. *Job Search Study: Literature Review and Analysis of the Labour Force Survey*. London: Department for Work and Pensions Research Report, p. 726.

Gross-Gołacka, Elwira, Marta Kusterka-Jefmańska, and Bartłomiej Jefmański. 2020. Can Elements of Intellectual Capital Improve Business Sustainability?—The Perspective of Managers of SMEs in Poland. *Sustainability* 12: 1545. [CrossRef]

Guo, Wenchen, Hongjun Xiao, and Xi Yang. 2012. An Empirical Research on the Correlation between Human Capital and Career Success of Knowledge Workers in Enterprise. *Physics Procedia* 25: 715–25. [CrossRef]

Haenggli, Madeleine, and Andreas Hirschi. 2020. Career Adaptability and Career Success in the Context of a Broader Career Resources Framework. *Journal of Vocational Behavior* 119: 103414. [CrossRef]

Hasan, Karwan Kamal. 2021. The Relationship between Intellectual Capital and Organizational Trust and Its Impact on Achieving the Requirements of Entrepreneurship Strategy (The Case of Korek Telecom Company, Iraq). *International Journal of Multicultural and Multireligious Understanding* 8: 130–46. [CrossRef]

Hitka, Miloš, Alžbeta Kucharčíková, Peter Štarchoň, Ž. Balážová, Michal Lukáč, and Zdenko Stacho. 2019. Knowledge and Human Capital as Sustainable Competitive Advantage in Human Resource Management. *Sustainability* 11: 4985. [CrossRef]

Hu, Zhining. 2021. The Effect of Income Inequality on Human Capital Inequality: Evidence from China. *Structural Change and Economic Dynamics* 58: 471–89. [CrossRef]

Huang, Chao-Chin, and Shyh-Ming Huang. 2020. External and Internal Capabilities and Organizational Performance: Does Intellectual Capital Matter? *Asia Pacific Management Review* 25: 111–20. [CrossRef]

Huđek, Ivona, Polona Tominc, and Karin Širec. 2021. The Impact of Social and Cultural Norms, Government Programs and Digitalization as Entrepreneurial Environment Factors on Job and Career Satisfaction of Freelancers. *Sustainability* 13: 779. [CrossRef]

Hyytinen, Ari, Pekka Ilmakunnas, Edvard Johansson, and Otto Toivanen. 2019. Heritability of Lifetime Earnings. *Journal of Economic Inequality* 17: 319–35. [CrossRef]

Ichim, George Marian. 2020. Organisational Culture in Romania: The Fine Line between Success and Failure for Women in Academia. *Stanovnistvo* 58: 23–41. [CrossRef]

Kao, Chihwa. 1999. Spurious Regression and Residual-Based Tests for Cointegration in Panel Data. *Journal of Econometrics* 90: 1–44. [CrossRef]

Koch, Michael, Sarah Park, and Shaker A. Zahra. 2021. Career Patterns in Self-Employment and Career Success. *Journal of Business Venturing* 36: 105998. [CrossRef]

Kocsis, David, and Jason Xiong. 2022. A Divide Quantified—Exploring the Relationship between ICT Infrastructure Diffusion and Income Inequality. *Journal of Electronic Business & Digital Economics* 1: 34–49. [CrossRef]

Kose, Nezir, Festus Victor Bekun, and Andrew Adewale Alola. 2020. Criticality of Sustainable Research and Development-Led Growth in EU: The Role of Renewable and Non-Renewable Energy. *Environmental Science and Pollution Research* 27: 12683–91. [CrossRef] [PubMed]

Kranefeld, Iris, and Gerhard Blickle. 2021. Emotion Recognition Ability and Career Success: Assessing the Roles of GMA and Conscientiousness. *Personality and Individual Differences* 168: 110370. [CrossRef]

Lasisi, Taiwo Temitope, Kayode Kolawole Eluwole, Ali Ozturen, and Turgay Avci. 2019. Explanatory Investigation of the Moderating Role of Employee Proactivity on the Causal Relationship between Innovation-Based Human Resource Management and Employee Satisfaction. *Journal of Public Affairs* 20: e2051. [CrossRef]

Lasisi, Taiwo Temitope, Ali Ozturen, Kayode Kolawole Eluwole, and Turgay Avci. 2020. Explicating Innovation-Based Human Resource Management's Influence on Employee Satisfaction and Performance. *Employee Relations: The International Journal* 42: 1181–203. [CrossRef]

Lazareva, Elena, Tatiana Anopchenko, and Anton Murzin. 2018. Human Capital in the System of Urban Territory Sustainable Development Management. Paper presented at the Smart and Sustainable Cities Conference, Moscow, Russia, May 23–26; pp. 269–77. [CrossRef]

Lazareva, Elena I., Tatiana Y. Anopchenko, and Anton D. Murzin. 2020a. Human Potential Increment in the System of Innovative Economy Sustainable Development Management. In Paper presented at the Inclusive Development of Society: Proceedings of the 6th International Conference on Management and Technology in Knowledge, Service, Tourism & Hospitality (SERVE 2018), Rostov-on-don, Russia, December 15–16; p. 114.

Lazareva, Elena, Olga Gorbaneva, Anton Murzin, and Evgeniya Roshchina. 2020b. Socio-Ecological Potential Increment in the System of Innovation Economy Sustainable Management. Paper presented at the 2020 2nd International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency (SUMMA), Lipetsk, Russia, November 11–13; pp. 195–200.

Lazazzara, Alessandra, Edoardo della Torre, and Raoul C. D. Nacamulli. 2020. Understanding the Relationship Between Intellectual Capital and Organizational Performance: The Role of e-HRM and Performance Pay. In *Exploring Digital Ecosystems*. Berlin/Heidelberg: Springer, pp. 151–64.

Mansoor, Adil, Sarwat Jahan, and Madiha Riaz. 2021. Does Green Intellectual Capital Spur Corporate Environmental Performance through Green Workforce? *Journal of Intellectual Capital* 22: 823–39. [CrossRef]

Martins, Vitor Willia, Batista Izabela Simon, Rampasso Rosley Anholon, Osvaldo Luiz Goncalves Quelhas, and Walter Leal Filho. 2019. Knowledge Management in the Context of Sustainability: Literature Review and Opportunities for Future Research. *Joural of Cleaner Production* 229: 489–500. [CrossRef]

Masud, Muhammad Mehedi, Fatimah Binti Kari, Hasanul Banna, and Md. Khaled Saifullah. 2018. Does Income Inequality Affect Environmental Sustainability? Evidence from the ASEAN-5. *Journal of Asia Pacific Economy* 23: 213–28. [CrossRef]

Matos, Florinda, and Valter Martins Vairinhos. 2017. Intellectual Capital Management as a Driver of Competitiveness and Sustainability. *Journal of Intellectual Capital* 18: 466–69. [CrossRef]

Muwardi, Didi, Saide Saide, Richardus Eko Indrajit, Mohammad Iqbal, Endang Siti Astuti, and Herzavina Herzavina. 2020. Intangible Resources and Institution Performance: The Concern of Intellectual Capital, Employee Performance, Job Satisfaction, and Its Impact on Organization Performance. *International Journal of Innovation Management* 24: 2150009. [CrossRef]

Naseer, Memoona, Atif Mahmood, and Sara Kanwal. 2015. Impact of Career Success on Organizational Performance: A Study of Health Care Sector. *Pakistan Journal of Commerce and Social Sciences (PJCSS)* 9: 742–60.

Pedroni, Peter. 1999. Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. *Oxford Bulletin of Economic Statistics* 61: 653–70. [CrossRef]

Pesaran, M. Hashem, Yongcheol Shin, and Ron P. Smith. 1999. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association* 94: 621–34. [CrossRef]

Phillips, Peter C. B., and Pierre Perron. 1988. Testing for a Unit Root in Time Series Regression. *Biometrika* 75: 335–46. [CrossRef]

Pico-Saltos, Roberto, David Sabando-Vera, Marcela Yonfa-Medranda, Javier Garzás, and Andrés Redchuk. 2023. Hierarchical Component Model (HCM) of Career Success and the Moderating Effect of Gender, from the Perspective of University Alumni: Multigroup Analysis and Empirical Evidence from Quevedo, Ecuador. *Sustainability* 15: 540. [CrossRef]

Pitesa, Marko, and Madan M. Pillutla. 2019. Socioeconomic Mobility and Talent Utilization of Workers from Poorer Backgrounds: The Overlooked Importance of Within-Organization Dynamics. *Academy of Management Annals* 13: 737–69. [CrossRef]

Pordelan, Nooshin, and Simin Hosseinian. 2021. Online Career Counseling Success: The Role of Hardiness and Psychological Capital. *International Journal for Educational and Vocational Guidance* 21: 531–49. [CrossRef] [PubMed]

Razzaq, Asif, Arshian Sharif, Paiman Ahmad, and Kittisak Jermsittiparsert. 2021. Asymmetric Role of Tourism Development and Technology Innovation on Carbon Dioxide Emission Reduction in the Chinese Economy: Fresh Insights from QARDL Approach. *Sustainable Development* 29: 176–93. [CrossRef]

Roztocki, Narcyz, Piotr Soja, and Heinz Roland Weistroffer. 2019. The Role of Information and Communication Technologies in Socioeconomic Development: Towards a Multi-Dimensional Framework. *Information Technology for Development* 25: 171–83. [CrossRef]

Salvi, Antonio, Filippo Vitolla, Anastasia Giakoumelou, Nicola Raimo, and Michele Rubino. 2020. Intellectual Capital Disclosure in Integrated Reports: The Effect on Firm Value. *Technological Forecasting and Social Change* 160: 120228. [CrossRef]

Sanchez-García, Maria Fe, and Magdalena Suárez-Ortega. 2021. Professional Success and Satisfaction in the Career Development: Gender Patterns. *Revista de Investigación Educativa* 39: 31–48. [CrossRef]

Sanchez-Gomez, Martin, Edgar Breso, and Gabriele Giorgi. 2021. Could Emotional Intelligence Ability Predict Salary? A Cross-Sectional Study in a Multioccupational Sample. *International Journal of Environmental Research and Public Health* 18: 1322. [CrossRef]

Secundo, Giustina, Valentina Ndou, Pasquale del Vecchio, and Gianluigi de Pascale. 2020. Sustainable Development, Intellectual Capital and Technology Policies: A Structured Literature Review and Future Research Agenda. *Technological Forecasting and Social Change* 153: 119917. [CrossRef]

Sharma, Sarishma, and Khushdeep Dharni. 2017. Intellectual Capital Disclosures in an Emerging Economy: Status and Trends. *Journal of Intellectual Capital* 18: 868–83. [CrossRef]

Sheikh, Aarif Mohd. 2021. Green Intellectual Capital and Social Innovation: The Nexus. *Journal of Intellectual Capital*. *ahead-of-print*. [CrossRef]

Shen, Chengfang, and Xindong Zhao. 2022. How Does Income Inequality Affects Economic Growth at Different Income Levels? *Economic Research-Ekonomska Istraživanja*, 1–22. [CrossRef]

Shockley, Kristen M., Heather Ureksoy, Ozgun Burcu Rodopman, Laura F. Poteat, and Timothy Ryan Dullaghan. 2016. Development of a New Scale to Measure Subjective Career Success: A Mixed-Methods Study. *Journal of Organizational Behavior* 37: 128–53. [CrossRef]

Silva, Ana, Cecilia Tomassini, Julieta Zurbrigg, Adrián G. Palacios, Verónica Amarante, and Cecilia Bouzat. 2021. Gender Inequality in Latin American Neuroscience Community. *IBRO Neuroscience Reports* 10: 104–8. [CrossRef] [PubMed]

Simonova, Marina V, Lidya P. Bazhutkina, and Vladmir A. Berdnikov. 2015. Approaches to the System Salary Increase in the Region on the Ground of Labor Production Growth. *Review of European Studies* 7: 58. [CrossRef]

Spurk, Daniel, Annabelle Hofer, and Simone Kauffeld. 2021. Why Does Competitive Psychological Climate Foster or Hamper Career Success? The Role of Challenge and Hindrance Pathways and Leader-Member-Exchange. *Journal of Vocational Behavior* 127: 103542. [CrossRef]

Steinfield, Charles, Ada Scupola, and Carolina López-Nicolás. 2010. Social Capital, ICT Use and Company Performance: Findings from the Medicon Valley Biotech Cluster. *Technological Forecasting and Social Change* 77: 1156–66. [CrossRef]

Suciu, Marta-Christina, and Diana-Florentina Năsulea. 2019. Intellectual Capital and Creative Economy as Key Drivers for Competitiveness towards a Smart and Sustainable Development: Challenges and Opportunities for Cultural and Creative Communities. In *Intellectual Capital Management as a Driver of Sustainability*. Berlin/Heidelberg: Springer, pp. 67–97.

Sutrisno, Sutrisno. 2021. Intellectual Agility Stimulation to Improve Organizational Performance. *Budapest International Research and Critics Institute (BIRCI-Journal): Humanities and Social Sciences* 4: 1397–409. [CrossRef]

United Nations Development Programme Reports and Publications. 2021. Available online: https://hdr.undp.org/reports-and-publications (accessed on 13 January 2023).

Valk, Reimara, Marloes L. van Engen, and Mandy van der Velde. 2014. International Careers and Career Success of Indian Women in Science and Technology: The Importance of Career Capital and Organizational Capital. *South Asian Journal of Human Resources Management* 1: 175–205. [CrossRef]

van der Heijde, Claudia M., and Beatrice I. J. M. van der Heijden. 2014. Employability and Social Innovation: The Importance of and Interplay between Transformational Leadership and Personality. *Human Resource Management, Social Innovation and Technology Advanced Series in Management* 14: 55–72. [CrossRef]

Waldmüller, Johannes M., Hameed Jamali, and Nelson Nogales. 2019. Operationalizing Sustainable Development Goals in Vulnerable Coastal Areas of Ecuador and Pakistan: Marginalizing Human Development? *Journal of Human Development and Capabilities* 20: 468–85. [CrossRef]

Wang, Yao-Fen. 2013. Constructing Career Competency Model of Hospitality Industry Employees for Career Success. *International Journal of Contemporary Hospitality Management* 25: 994–1016. [CrossRef]

Werts, Charles E., Karl G. Jöreskog, and Robert L. Linn. 1971. Comment on" The Estimation of Measurement Error in Panel Data". *American Sociology Review* 36: 110–13. [CrossRef]

World Bank. 2010. Metadata Glossary. Available online: https://databank.worldbank.org/metadataglossary/jobs/series/NY.GDP.PCAP.KD (accessed on 13 January 2023).

Yu, Jiaju, and Ye Xu. 2022. Income Inequality and Human Capital Allocation. *Economic Research-Ekonomska Istraživanja*, 1–16. [CrossRef]