“The role of R&D expenditure and human capital in shaping economic growth: A time series analysis of Hong Kong”

AUTHORS	Zeynab Giyasova Muslum Mursalov Jeyhun Hajiyev Nelson Amowine Gunay Panahova

ARTICLE INFO	Zeynab Giyasova, Muslum Mursalov, Jeyhun Hajiyev, Nelson Amowine and Gunay Panahova (2025). The role of R&D expenditure and human capital in shaping economic growth: A time series analysis of Hong Kong. *Problems and Perspectives in Management*, *23*(3), 218-231. doi:10.21511/ppm.23(3).2025.16
DOI	http://dx.doi.org/10.21511/ppm.23(3).2025.16
RELEASED ON	Tuesday, 12 August 2025
RECEIVED ON	Monday, 14 April 2025
ACCEPTED ON	Tuesday, 29 July 2025

JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Zeynab Giyasova (Azerbaijan), **Muslum Mursalov** (Azerbaijan), **Jeyhun Hajiyev** (Azerbaijan), **Nelson Amowine** (China), **Gunay Panahova** (Azerbaijan)

THE ROLE OF R&D EXPENDITURE AND HUMAN CAPITAL IN SHAPING ECONOMIC GROWTH: A TIME SERIES ANALYSIS OF HONG KONG

Abstract

This study investigates the causal relationship between research and development (R&D) financing and economic growth in Hong Kong over the period 1998–2022. It examines both public and private R&D expenditures, along with the number of researchers involved in R&D, to evaluate their influence on GDP per capita. Utilizing advanced time series econometric techniques, including the Toda-Yamamoto causality approach and cointegration analysis, the results reveal a statistically significant unidirectional causality from R&D expenditure to GDP per capita ($\chi^2 = 26.443$, $p < 0.01$) and from researchers in R&D to GDP per capita ($\chi^2 = 38.164$, $p < 0.01$). Additionally, feedback effects were observed, with GDP per capita also causing R&D expenditure ($\chi^2 = 17.471$, $p < 0.01$), and R&D expenditure influencing the number of researchers ($\chi^2 = 6.718$, $p < 0.01$). These findings highlight the dynamic interplay between financial inputs and human capital in R&D and underscore the importance of sustained investment and a skilled research workforce in fostering long-term economic growth. The evidence supports the strategic role of R&D policy in enhancing productivity and promoting economic sustainability in knowledge-based economies.

Keywords R&D, economic growth, human capital, econometrics, time series, Hong Kong

JEL Classification O15, C32, E22

Type of article: Research Article

Received on: 14th of April, 2025
Accepted on: 29th of July, 2025
Published on: 12th of August, 2025

Zeynab Giyasova, Ph.D., Azerbaijan State University of Economics (UNEC); Azerbaijan Technical University, Azerbaijan. (Corresponding author)

Muslum Mursalov, Ph.D., Assistant Professor, Department of Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan.

Jeyhun Hajiyev, Ph.D., Department of Economics and Statistics, Azerbaijan Technical University; Azerbaijan State University of Economics (UNEC), Azerbaijan.

Nelson Amowine, Ph.D., Department of Law and Public Administration, Yibin University, China.

Gunay Panahova, Ph.D., Associate Professor, Department of Economics, Azerbaijan State University of Economics (UNEC), Azerbaijan.

Conflict of interest statement:
Author(s) reported no conflict of interest

INTRODUCTION

Human capital, defined by the scientific workforce's knowledge, skills, and experience, is pivotal in driving economic growth by enhancing productivity, fostering innovation, and improving technological capabilities. Education and skill development investments are essential for cultivating a competitive labor force that underpins long-term sustainable growth and economic development (Che Sulaiman et al., 2021). As economies shift toward knowledge-based industries, the relationship between human capital, R&D, and economic growth has become increasingly important. This study examines how R&D investment and researcher capacity contribute to economic growth in Hong Kong, providing empirical support for innovation-driven growth models.

Over the past few decades, Hong Kong has undergone a notable transition towards knowledge-intensive industries, with innovation playing a critical role in driving its economic transformation. The integration of R&D activities into the economic framework has been vital in boosting productivity and fostering sustainable development (Chan, 2012; Shi et al., 2024). Human capital, as a fundamental driver in this process, has shaped the region's development by enhancing innovation capacity and increasing the technological capabilities of the work-

http://dx.doi.org/10.21511/ppm.23(3).2025.16

force. According to the "Hong Kong Innovation Activities Statistics 2022" report, the gross domestic expenditure on research and development (GERD) reached HK$30,138 million in 2022, marking an 8% increase from the previous year and pushing the GERD-to-GDP ratio to 1.07% (HKIAS, 2023). The government's commitment to fostering innovation is evident in its various initiatives, including advancing microelectronics and artificial intelligence R&D, supporting the Hetao Shenzhen-Hong Kong Science and Technology Innovation Cooperation Zone, and launching the RAISe+ Scheme to commercialize R&D outcomes.

The dynamic enhancement of supply chain management is integral to economic progress, and scientific research constitutes a key foundation for achieving sustainable industrial development and implementing green design across various domains (Lu et al., 2024; Hasanov & Safarli, 2023; Hasanov, 2023). Broadly speaking, the role of human capital and investment has gained critical importance in advancing the sustainability of China's economic development (Park, 2018). In addition to direct investments in R&D, the government has introduced several measures to encourage R&D activities in the business sector. These include the establishment of R&D centers, technology parks, tax incentives, and dedicated funding schemes under the Innovation and Technology Fund (ITF). By the end of 2022, the ITF had approved HK$32.8 billion across 17 funding schemes, with approximately half allocated to supporting R&D activities. Despite this, businesses still primarily finance their own R&D efforts or rely on funding from affiliates or parent companies (ITB, 2023). The relationship between human capital and innovation has been explored in Hong Kong, where human capital development is recognized as a key factor in economic growth and development. However, scholars such as Lai and Maclean (2011) have pointed out that, until 2009, efforts to attract foreign talent often overshadowed strategies to build a sustainable education system, raising questions about aligning this approach with Hong Kong's ambition of transitioning to a knowledge-based economy.

R&D expenditure and human capital are widely recognized as critical drivers of economic growth in knowledge-based economies. However, existing empirical studies tend to concentrate on developed Western nations or major Asian economies such as China, Japan, and South Korea, with limited attention paid to smaller high-income regions like Hong Kong (Chandra et al., 2018). As Hong Kong transitions toward an innovation-led growth model, understanding the economic impact of R&D investment and skilled research personnel becomes increasingly important. Despite policy efforts to foster innovation, empirical evidence on how these inputs influence economic performance remains scarce. This study addresses this gap by exploring the relevance of R&D and human capital in shaping growth within the unique context of Hong Kong's open and structurally evolving economy.

1. LITERATURE REVIEW

Exploring the connections among R&D, human capital, and economic growth has become a significant area of inquiry within development economics, leading to a broad spectrum of theoretical and empirical research across various national and regional contexts. The role of R&D in driving economic growth has also been examined in comparative studies. Sharif et al. (2021) analyzed the impact of R&D expenditure on total factor productivity (TFP) growth in Hong Kong, Shenzhen, and Singapore. Their results indicated that while public and private R&D contributed to TFP growth, their effects varied significantly across the regions. Hong Kong showed limited but significant growth, Shenzhen showed no significant impact, and Singapore experienced robust and positive growth. Chen et al. (2020) further explored the role of foreign investors as signals in reducing information asymmetry and enhancing the efficiency of government R&D subsidies. Their study highlighted that those enterprises targeted by the Shanghai-Hong Kong Stock Connect received more R&D subsidies, with smaller firms, high-tech industries, and those with a high proportion of intangible assets benefiting the most. Scholars worldwide have focused on the dependencies and interrelationships between R&D, human capital, and economic development. Pelinescu (2015) analyzed the EU's 2020 Strategy, which focused on three areas of growth: smart, sustainable, and inclusive, and emphasized that these goals could not have been achieved without the significant contribution of human capital, including skills and knowledge. Using panel methodology, the paper examined the role of human capital as a driver of growth and argued that slow investment in human capital had the potential to hinder the sustainable development of countries. Agarwalla and Sahu (2024) analyzed the impact of human capital and innovation on economic growth in 54 developing economies, finding that government spending on health and education fosters growth, while tertiary enrollment has a short-term negative effect. The study also highlighted the positive role of eco-friendly innovation and emphasized the need for policies prioritizing human capital development to enhance overall economic performance. Carillo (2024) examined the impact of human capital composition on technological progress, suggesting that the balance between higher and lower education levels influenced innovation and technology adoption, which in turn affected economic growth and income disparities. The study provided empirical evidence that technology adoption complements technological progress and emphasized the importance of human capital composition in shaping education reforms for economic development. In addition to the established scientific studies referenced, Table 1 presents other relevant research examples related to the topic.

Several scientific studies have been conducted on similar topics in Hong Kong, which serves as the primary focus of the current research. Lung Ka-Lun (2012) analyzed Hong Kong's potential for transitioning into a high-value-added, knowledge-based economy, with a focus on its evolution since reunification with China. The study emphasizes

Table 1. Overview of studies on R&D, human capital, and economic growth

No.	Author(s)	Country/Region	Main Findings	Methodology
1	Bilbao-Osorio and Rodríguez-Pose (2004)	European Union (Peripheral Regions)	Investigates the impact of R&D investments on innovation and economic growth in peripheral regions of Europe.	Two-step analysis: Impact of R&D on innovation and the effect of innovation on economic growth.
2	Hu et al. (2007)	Hebei Province (China)	The DEA model is used to study R&D structure and efficiency in Hebei Province and its impact on economic growth.	DEA model for R&D structure and efficiency analysis.
3	Pessoa (2010)	OECD Countries	Examines the relationship between R&D outlays and economic growth, questioning the effectiveness of innovation policies based on increasing R&D intensity.	Argument-based analysis with data comparison
4	Park (2018)	China	Examines the interaction between FDI, R&D, and human capital and their impact on economic growth.	Data mining, semantic network analysis (SNA), and Vector Error Correction Model (VECM).
5	Chu and Cozzi (2014)	Theoretical Analysis (Schumpeterian Model)	Analyzes the effects of monetary policy on economic growth and social welfare, focusing on R&D investment in a Schumpeterian growth model with CIA constraints.	Schumpeterian growth model with cash-in-advance (CIA) constraints.
6	Bayarcelik and Taşel (2012)	Turkey	Investigates the relationship between innovation and economic growth in Turkey using R&D data from chemical firms listed on the Istanbul Stock Exchange.	Panel regression model analysis.
7	Edquist and Henrekson (2017)	Sweden	Investigates the relationship between ICT and R&D capital with value-added growth in Sweden's business sector.	Output elasticity estimation, industry-level analysis, and growth accounting.
8	Mabrouki (2023)	Scandinavian Countries (Denmark, Finland, Iceland, Norway, Sweden)	Examines the effects of human capital, education, and patents on economic growth in Scandinavian countries from 1990 to 2019.	Panel cointegration tests, CS-ARDL model, Granger non-causality tests.
9	Chaabouni and Mbarek (2024)	17 European Countries	Analyzes the relationship between human capital (education and health) and economic growth, with differing results before and after COVID-19.	Empirical analysis with causal relationships between economic growth, education, and health.
10	Tung and Hoang (2024)	Emerging Economies	Studies the relationship between economic growth and national R&D expenditure in emerging economies.	Panel cointegration test, empirical analysis of long-run relationships.

http://dx.doi.org/10.21511/ppm.23(3).2025.16

the necessity for a supportive "horizontal" framework, the maintenance of free market policies, and a facilitation system to encourage high-value economic activities, offering a unique perspective on Hong Kong's future economic prospects within China's growing global influence. Chan (2022) examined the challenges associated with project valuation in Hong Kong, highlighting the necessity of transitioning towards an R&D-driven economy in the face of uncertainties and lagging private sector investment, especially in contrast to China. The study suggests utilizing established valuation frameworks, such as Net Present Value (NPV) and Net Options Value (NOV), within Hong Kong's public sector, offering an empirical analysis that aims to support economic restructuring and improve the city's competitive position through public sector R&D initiatives. Nevertheless, a gap exists in the exploration of the impact of human capital on economic development from a purely R&D and scientific perspective, highlighting the need for further research in this domain. Although extensive research has examined the relationship between R&D, human capital, and economic growth, significant theoretical gaps remain. Existing studies emphasize the role of human capital and innovation in economic development, but often consider human capital as a uniform construct. Insufficient attention has been given to the interaction between cognitive, technical, and creative skills in enhancing R&D efficiency and sustaining long-term growth, which may have distinct implications for technological progress and innovation adoption (Hanushek & Woessmann, 2015). While prior research has highlighted the influence of R&D and scientific human capital on economic growth, it often overlooks the nuanced role of skill diversity and innovation capacity. Although various aspects of Hong Kong's economic transformation have been studied, the specific impact of human capital composition within R&D-driven growth remains underexplored. This study aims to address this gap by advancing a comprehensive theoretical framework that captures the multifaceted nature of human capital and its critical role in supporting R&D-led economic development in Hong Kong. It is hypothesized that R&D expenditure exerts a positive causal effect on GDP per capita, and that the involvement of researchers in R&D activities significantly contributes to economic growth. Moreover, the analysis considers the possibility of a bidirectional relationship, where economic performance may, in turn, influence R&D investment and human capital development, indicating a feedback loop between innovation inputs and economic outcomes.

2. METHODOLOGY

The study explores the causal interplay between GDP per capita (LGDPPC), R&D expenditure (LRDE), and the number of researchers in R&D (LRRD) utilizing sophisticated econometric approaches. The analysis employs time series data for LGDPPC, LRDE, and LRRD, with each variable converted into its natural logarithmic form to stabilize variance and enhance linearity. The dataset, spanning the period from 1998 to 2022, is obtained from authoritative international and national sources, including the World Bank (2024), ensuring both accuracy and relevance.

The graphs in Figure 1 illustrate a positive trajectory in the nation's economic development. The consistent rise in GDP per capita reflects continuous economic expansion. Additionally, the upward trends in R&D expenditure and the number of researchers highlight an increasing focus on science and innovation. This investment in human capital and research will likely enhance productivity, boost competitiveness, and foster long-term economic prosperity.

Table 2 presents descriptive statistics summarizing the central tendency, dispersion, and distribution shape for three variables: GDPPC, RDE, and RRD. The mean values indicate average levels, while standard deviations show variability around the mean, with skewness highlighting the distribution asymmetry. GDPPC exhibits positive skewness, while RDE and RRD demonstrate negative skewness. Additionally, higher kurtosis values for RDE and RRD suggest heavier tails, indicating the presence of outliers, and these statistics provide a foundational understanding for further analysis of the relationships between the variables and their impact on economic growth and development.

The graphs illustrated in Figure 2 display the time series plots of the log-transformed variables LGDPPC, LRDE, and LRRD, all of which exhibit

Source: World Bank (2024).

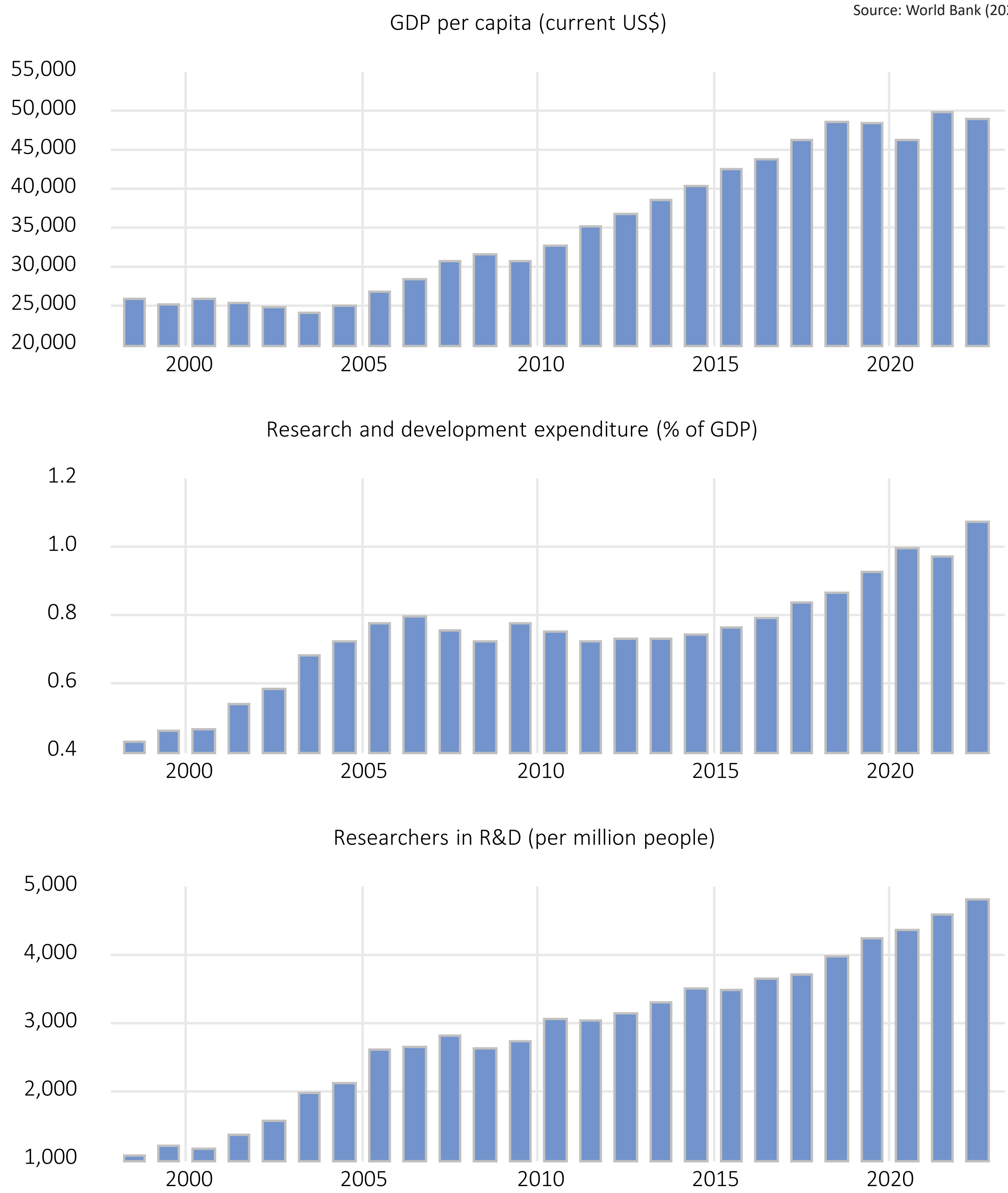

Figure 1. Trends in economic development:
GDP per capita, R&D expenditure, and researcher growth

Table 2. Statistical overview of the variables

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque–Bera
GDPPC	35208.54	32550.14	9258.69	0.290	1.551	2.539
RDE	0.742	0.749	0.160	–0.177	2.907	0.140
RRD	2902.39	3023.50	1098.95	–0.142	2.106	0.915

http://dx.doi.org/10.21511/ppm.23(3).2025.16

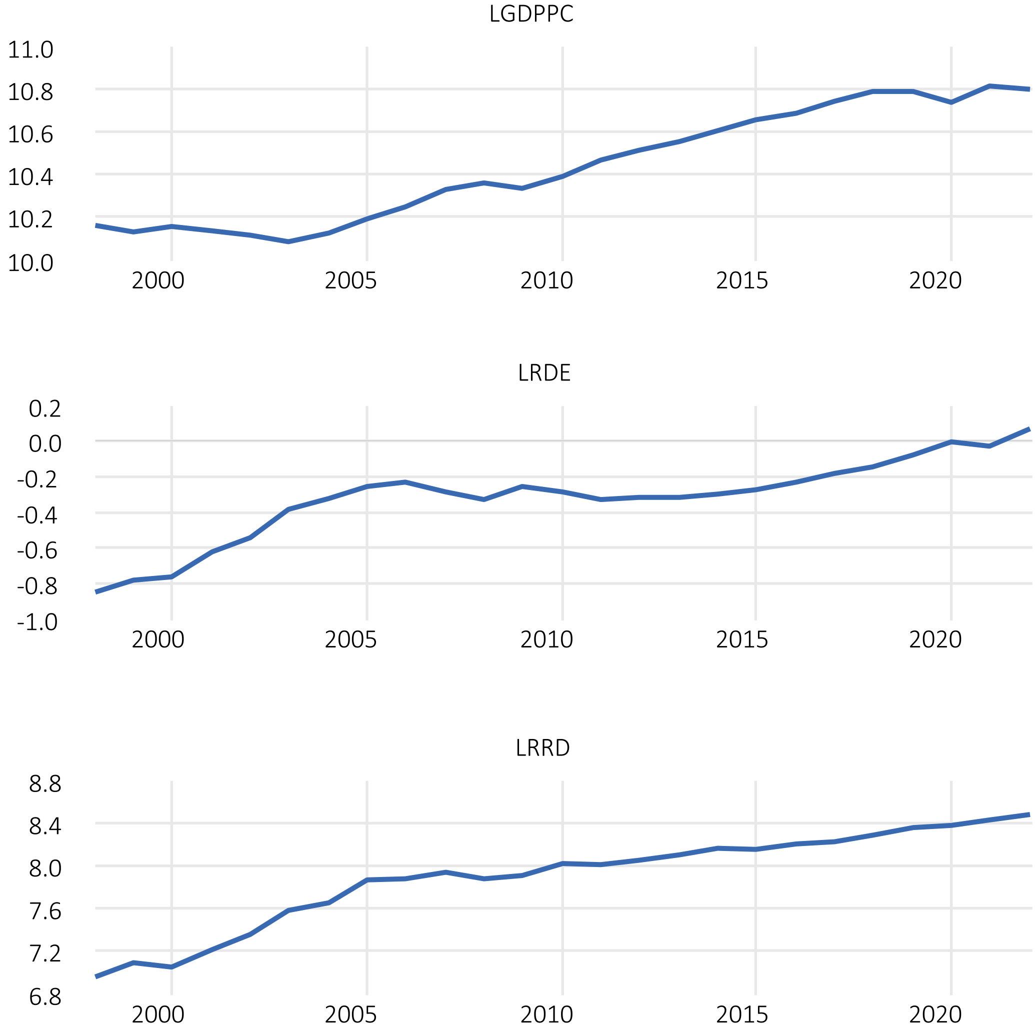

Figure 2. Visualizing growth dynamics: Log-transformed trends of LGDPPC, LRDE, and LRRD

upward trends. Specifically, LGDPPC indicates a pattern of consistent economic growth, while LRDE reflects an increasing, albeit fluctuating, trend in R&D expenditure, and LRRD demonstrates a rise in the number of researchers involved in R&D, highlighting a growing commitment to innovation. Employing a logarithmic scale accentuates relative changes and compresses large value ranges, which aids in the visualization of trends and growth rates.

To evaluate the stationarity of the variables, the Augmented Dickey-Fuller (ADF) tests (1981) and Phillips-Perron (PP) tests (1988) are utilized. These tests are crucial for determining the order of integration of the variables, which subsequently guides the choice of the appropriate econometric model. The ADF test, an extended version of the original Dickey-Fuller test, is employed to examine the presence of a unit root within the time series, incorporating lagged differences of the dependent variable to account for higher-order serial correlation. In contrast, the PP test, proposed by Phillips and Perron, is a non-parametric approach that adjusts for serial correlation and heteroskedasticity in the error terms without the inclusion of lagged differences.

The optimal lag length for the Vector Autoregression (VAR) model is selected based on several criteria, including the Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ). The findings suggest that a one-lag specification is optimal for effectively capturing the dynamic relationships among the variables while minimizing the risk of overfitting.

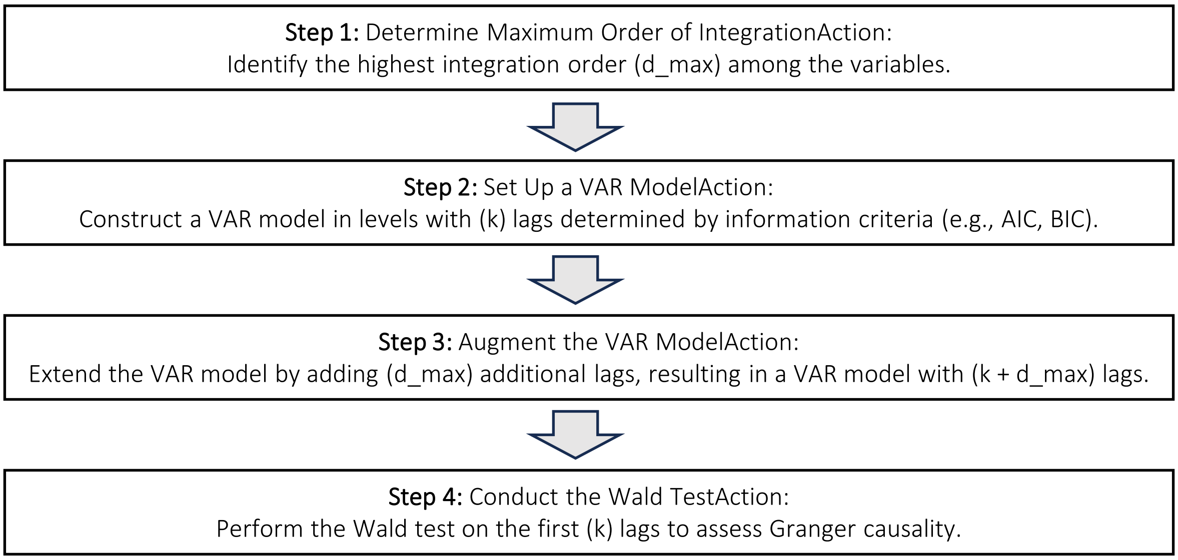

Figure 3. Procedural flowchart for conducting the Toda-Yamamoto Granger causality test

The stability and reliability of the VAR model are verified through diagnostic tests, with the inverse roots of the AR characteristic polynomial residing within the unit circle, thereby confirming model stability. Additionally, the Serial Correlation LM tests show no signs of serial correlation, affirming the independence of the residuals, while the Jarque-Bera test supports the normality of the residuals, and the heteroskedasticity test indicates consistent variance over time.

The Johansen cointegration test (1988) serves as a powerful method for examining long-term associations among several time series variables, especially when the data are non-stationary but share the same integration order. This approach employs two key statistical measures: the trace statistic and the maximum eigenvalue statistic to identify the number of cointegrating relationships present. The presence of at least one cointegrating equation, as determined by the trace and maximum eigenvalue tests, indicates stable, long-term relationships among the variables. This result is crucial for comprehending the system's dynamics and for developing econometric models that effectively represent these persistent connections.

The Toda-Yamamoto causality test (1995) is a refined econometric approach employed to assess causal linkages between variables, even when they exhibit different orders of integration. This technique is particularly beneficial as it bypasses the necessity for prior cointegration tests, reducing the likelihood of biases associated with pre-testing. Figure 3 illustrates the procedural steps for performing a Granger causality test. The process starts with identifying the maximum order of integration among the variables and constructing a VAR model with the optimal number of lags. The model is then augmented with additional lags corresponding to the highest integration order, culminating in the application of the Wald test on the initial lags to evaluate Granger causality.

The Toda-Yamamoto model is applied to the data variables empirically to test the proposed hypotheses. This study utilizes the following equations to derive insights and provide answers to the research questions.

$$\Delta GDPPC_t = \alpha + \beta RDE_t + \gamma \Delta RDE_{t-1} + \gamma_2 \Delta RDE_{t-2} + \gamma_3 \Delta RDE_{t-3} + \varepsilon_t. \quad (1)$$

$$\Delta GDPPC_t = \alpha + \beta RRD_t + \gamma \Delta RRD_{t-1} + \gamma_2 \Delta RRD_{t-2} + \gamma_3 \Delta RRD_{t-3} + \varepsilon_t. \quad (2)$$

$$\Delta RDE_t = \alpha + \beta GDPPC_t + \gamma \Delta GDPPC_{t-1} + \gamma_2 \Delta GDPPC_{t-2} + \gamma_3 \Delta GDPPC_{t-3} + \varepsilon_t. \quad (3)$$

$$\Delta RRD_t = \alpha + \beta RDE_t + \gamma \Delta RDE_{t-1} + \gamma_2 \Delta RDE_{t-2} + \gamma_3 \Delta RDE_{t-3} + \varepsilon_t. \quad (4)$$

http://dx.doi.org/10.21511/ppm.23(3).2025.16

3. RESULTS AND DISCUSSION

Table 3 presents the findings from the ADF and PP tests conducted to evaluate the order of integration for the variables LGDPPC, LRDE, and LRRD. The results reveal that LGDPPC and LRRD exhibit non-stationarity at the level but become stationary upon first differencing, categorizing them as integrated of order one, I(1). Conversely, LRDE is non-stationary at both the level and first difference, necessitating second differencing to achieve stationarity, thus classifying it as integrated of order two, I(2). Given the integration order of LRDE, the conventional Granger causality test (1969) is rendered inapplicable due to the non-stationarity of the variable at both the level and first difference. In such cases, the Toda-Yamamoto causality test is adopted as a robust alternative, which allows for the assessment of causal relationships in the presence of integrated variables. This methodology enriches the Vector Autoregression (VAR) model by incorporating additional lags beyond those typically dictated by the order of integration. Doing so ensures that the residuals from the model are stationary, which is essential for deriving valid statistical inferences regarding the causal dynamics among the variables under consideration. Ultimately, this approach facilitates a more comprehensive understanding of the variables' interactions, offering insights crucial for theoretical exploration and empirical analysis in economic research.

Table 4 presents the results of the optimal lag selection criteria, which collectively indicate that a one-lag model is the most suitable specification for the VAR analysis involving R&D expenditure, the number of researchers in R&D, and GDP per capita. Each criterion, including the Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), consistently identifies lag 1 as the optimal choice, suggesting that this specification effectively balances model dynamics with the risk of overfitting. The analysis reveals that incorporating additional lags beyond one does not significantly enhance model accuracy, indicating that the essential information and interactions among the variables are sufficiently captured with a single lag. As a result, the one-lag model minimizes complexity and enhances the interpretability of the relationships among the variables, which is critical for ensuring robust and parsimonious VAR modeling.

In forming a VAR model to apply the Toda-Yamamoto Granger causality test, the lag length (k) and maximum order of integration (dmax) must be considered. Here, d_{max} equals 2, as the variable LRDE is integrated of order 2 (I(2)). The relationship governing the model is expressed as $k+d_{max}=3$. By substituting dmax into this equation, k = 1. Therefore, the VAR model should include one lag of the variables, facilitating the accurate

Table 3. Unit root tests

Variable	Level	1st Difference	2nd Difference
The Augmented Dickey-Fuller (ADF)			
LGDPPC	–2.595 (0.285)	–3.674 (0.045*)	
LRDE	–3.353 (0.085)	–3.296 (0.091)	–4.862 (0.004*)
LRRD	1.790 (0.677)	–4.942 (0.003*)	
Phillips-Perron (PP)			
LGDPPC	–2.614 (0.277)	–3.681 (0.044*)	
LRDE	–1.995 (0.574)	–3.342 (0.084)	–8.063 (0.000*)
LRRD	–1.798 (0.673)	–4.950 (0.003*)	

Note: * indicates significance at the 5% level based on the MacKinnon et al. (1999).

Table 4. Var lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	40.40571	NA	7.76E-06	–3.252	–3.104563	–3.215
1	132.9278	152.862*	5.50e-09*	–10.515*	–9.923033*	–10.366*
2	140.1775	10.086	6.73E-09	–10.363	–9.326	–10.102

Note: * indicates lag order selected by the criterion.

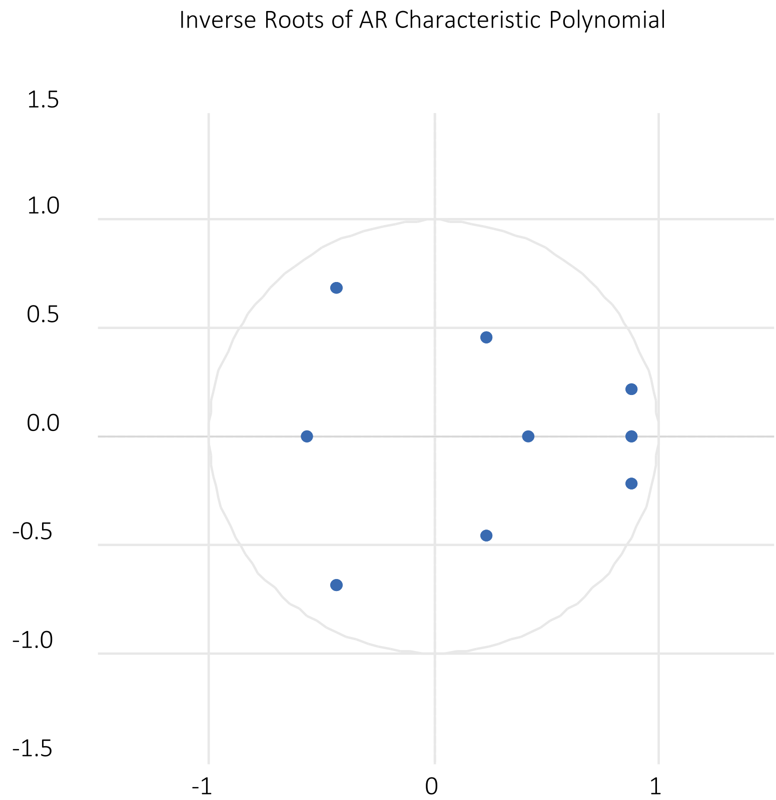

Figure 4. The inverse roots of the AR characteristic polynomial

testing of Granger causality while accounting for the integration characteristics of the variables involved.

In Figure 4, the Inverse Roots of the AR Characteristic Polynomial demonstrate that all roots reside within the unit circle, affirming the VAR model's stability. This stability guarantees that the model's estimates are reliable and devoid of explosive behavior, thus rendering it appropriate for robust analysis.

Table 5 presents the LM tests used to evaluate serial correlation in the residuals of the VAR model. Serial correlation occurs when residuals are correlated, contravening a key assumption of the VAR framework. In this analysis, p-values for all lags are greater than 0.05, leading to the conclusion that we cannot reject the null hypothesis of no serial correlation. This finding suggests that the residuals are independent, indicating the model's validity and enhancing its appropriateness for forecasting and policy analysis. The VAR Residual Serial Correlation LM Tests determine the residuals' independence from the VAR model.

Table 6 outlines the outcomes of the VAR Residual Diagnostic Tests, which evaluated the normality of the VAR model's residuals through skewness, kurtosis, and Jarque-Bera tests. The results indicate that the residuals are normally distributed both individually and collectively, an essential criterion since normality is a key assumption for many statistical tests used in VAR models. This normal distribution of residuals signifies that the model is well-specified, thereby enhancing the

Table 5. VAR residual serial correlation LM tests

Lag	LRE* stat	df	Prob.	Rao F-stat	df	P-value
1	10.4237	9	0.3173	1.251073	(9, 17.2)	0.329
2	7.308928	9	0.605	0.809265	(9, 17.2)	0.6145
3	9.721772	9	0.3735	1.145624	(9, 17.2)	0.3852
4	3.519543	9	0.9401	0.354171	(9, 17.2)	0.942

http://dx.doi.org/10.21511/ppm.23(3).2025.16

reliability of its forecasts. The Jarque-Bera test, which assesses the normality of residuals in the VAR context, yielded p-values for each component and the joint test greater than 0.05. Consequently, we fail to reject the null hypothesis of normality, further confirming the model's validity by indicating that the residuals adhere to a normal distribution. The VAR residual heteroskedasticity test assesses whether the variance of the residuals remains constant over time. In this instance, the joint test yielded a p-value of 0.2941, exceeding the significance level of 0.05. This outcome indicates that we do not reject the null hypothesis of homoskedasticity, implying that the residuals' variance is stable across time periods. Such stability indicates the model's validity, reinforcing its appropriateness for subsequent analysis and forecasting.

Table 6. VAR residual diagnostic tests

Normality Test			
Component	**Jarque-Bera**	**df**	**P-value**
1	0.147	2	0.928
2	0.415	2	0.812
3	1.490	2	0.474
Joint test	2.053	6	0.914
Heteroskedasticity Test			
Joint test	**Chi-sq**	**df**	**P-value**
	115.461	108	0.294

Table 7 presents the findings from the Johansen Cointegration Test, which investigates the long-term relationship among LGDPPC, LRDE, and LRRD. The trace test reveals two cointegrating equations at the 0.05 significance level (p-value = 0.0062), while the maximum eigenvalue test indicates only one cointegrating equation (p-value = 0.0849). Given the divergence in these results, it is essential to incorporate economic theory and conduct further analysis to ascertain the appropriate number of cointegrating equations. Nevertheless, the findings suggest that at least one long-run relationship exists among the variables, which is important as it implies that fluctuations in one variable will have enduring effects on the others. The outcomes of the Johansen cointegration test are in line with previous studies that have applied similar methods to explore long-term relationships between economic variables, thus reinforcing the effectiveness and reliability of cointegration techniques in empirical analysis (Tuna et al., 2015; Dritsaki & Dritsaki, 2023).

Table 8 presents the findings of the Toda-Yamamoto Granger causality test, a robust technique for assessing causal relationships among non-stationary time series variables. This methodology effectively addresses potential biases associated with spurious regression when working with non-stationary data. The results indicate the following causal relationships:

- R&D Expenditure and GDP per Capita: R&D expenditure Granger causes GDP per capita, suggesting that variations in R&D spending occur prior to changes in GDP per capita. This highlights the significant influence of R&D investment on economic growth.

- Researchers in R&D and GDP per Capita: The results demonstrate that researchers in R&D Granger cause GDP per capita, indicating that an increase in researchers correlates with subsequent growth in GDP per capita, thereby underscoring the importance of human capital in driving economic development.

- GDP per Capita and R&D Expenditure: Additionally, GDP per capita Granger causes R&D expenditure, suggesting that as the economy expands, there is an inclination to allocate more resources to R&D efforts.

- R&D Expenditure and Researchers in R&D: Finally, R&D expenditure Granger causes the number of researchers in R&D, implying that greater investment in R&D promotes the growth of the research workforce.

Table 7. Johansen cointegration test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	P-value	Max-Eigen Statistic	0.05 Critical Value	P-value
None	0.852	56.553	29.797	0.000*	40.130	21.131	0.000*
At most 1	0.455	16.422	15.494	0.036*	12.770	14.264	0.084
At most 2	0.159	3.652	3.8414	0.056	3.652	3.841	0.056

Note: * denotes rejection of the hypothesis at the 0.05 level.

Table 8. Toda-Yamamoto Granger causality test

Null hypothesis	Lag (k)	K + Dmax	Chi-squared test	Result
R&D expenditure (RDE) does not cause to GDP per capita (GDPPC)	1	3	26.443 (0.000*)	Reject
Researchers in R&D (RRD) do not cause GDP per capita (GDPPC)	1	3	38.164 (0.000*)	Reject
GDP per capita (GDPPC) does not cause R&D expenditure (RDE)	1	3	17.471 (0.000*)	Reject
R&D expenditure (RDE) does not cause Researchers in R&D (RRD)	1	3	6.718 (0.001*)	Reject

Note: ** denotes rejection of the hypothesis at the 0.01 level.

The Granger causality test results provide significant insights into the dynamic interactions between R&D, human capital, and economic growth. These findings suggest that implementing policies to bolster R&D investment and develop a strong research workforce can be instrumental in promoting sustained economic development. The findings derived from the Granger causality test are in line with previous research employing analogous methodologies to examine causal interactions among economic variables, thereby substantiating the reliability of this approach in empirical analyses and underscoring its utility in discerning the direction of causality (Hong, 2017; Islam, 2025). This study extends the work of Boeing et al. (2022) by reaffirming the significant impact of R&D investments on economic growth while emphasizing the vital role of human capital composition in driving innovation, beyond the partial crowding-out effects documented in Chinese provinces. In contrast to Jalil et al. (2024), who focus on financial development and regulatory influences on knowledge creation in emerging economies, this research highlights the importance of skill diversity and its direct contribution to R&D-led growth within Hong Kong's advanced innovation landscape. Collectively, these results suggest that successful economic growth policies should integrate both strategic R&D funding and the cultivation of diverse human capital to promote sustainable, innovation-driven development.

This study highlights the importance of R&D expenditure and human capital in promoting sustained economic growth, presenting key policy considerations. Policymakers should prioritize boosting R&D funding through direct financial support, tax incentives, and grants for both public and private research entities, while simultaneously investing in human capital by enhancing educational and training programs to cultivate a skilled research workforce. Additionally, fostering innovation through policies that safeguard intellectual property and encourage entrepreneurship can amplify the effectiveness of R&D investments. Despite the valuable insights, data constraints and the inherent complexities of causality may limit the study's conclusions, and the assumptions underlying the model may not be universally applicable. Future research should aim to expand data sets, focus on sector-specific analyses, and conduct cross-country comparative studies for deeper understanding. Incorporating other factors such as government policies, international trade, and technological advancements could provide a more comprehensive view of the factors influencing economic growth.

CONCLUSION

This study examined the dynamic relationship between GDP per capita, R&D expenditure, and the number of researchers to assess their collective influence on economic growth. The results of the Johansen cointegration test provide robust evidence of a statistically significant long-term equilibrium among these variables. In particular, the trace statistic (56.553) and the maximum eigenvalue statistic (40.130) for the null hypothesis of no cointegration exceed the 5% critical values, with p-values of 0.000, confirming the presence of at least one cointegrating vector. Complementing this, the Toda-Yamamoto causality analysis reveals a unidirectional causal flow from both R&D expenditure and the number of researchers to GDP per capita, indicating that innovation-related inputs play a critical role in driving economic growth. Moreover, evidence of reverse causality from economic performance to R&D activity underscores the presence of a reinforcing feedback mechanism. Collectively, these findings high-

http://dx.doi.org/10.21511/ppm.23(3).2025.16

light the bidirectional and mutually enhancing relationship between innovation capacity and economic development. The results underscore the imperative for coherent and sustained policy strategies that simultaneously prioritize investment in R&D and the cultivation of research-intensive human capital. To advance this line of inquiry, future research should expand the analytical framework by integrating sector-specific dynamics, cross-country comparisons, and additional explanatory variables such as institutional quality, regulatory frameworks, and technological diffusion to deepen the understanding of growth trajectories in innovation-driven economies.

AUTHOR CONTRIBUTIONS

Conceptualization: Zeynab Giyasova, Muslum Mursalov.
Data curation: Zeynab Giyasova, Jeyhun Hajiyev, Nelson Amowine.
Formal analysis: Muslum Mursalov, Jeyhun Hajiyev, Nelson Amowine, Gunay Panahova.
Funding acquisition: Gunay Panahova.
Investigation: Zeynab Giyasova, Muslum Mursalov, Nelson Amowine.
Methodology: Zeynab Giyasova.
Project administration: Zeynab Giyasova, Muslum Mursalov, Jeyhun Hajiyev.
Resources: Jeyhun Hajiyev, Gunay Panahova.
Software: Zeynab Giyasova.
Supervision: Muslum Mursalov, Jeyhun Hajiyev, Nelson Amowine, Gunay Panahova.
Validation: Jeyhun Hajiyev, Nelson Amowine, Gunay Panahova.
Visualization: Zeynab Giyasova.
Writing – original draft: Zeynab Giyasova.
Writing – review & editing: Muslum Mursalov, Jeyhun Hajiyev, Nelson Amowine, Gunay Panahova.

REFERENCES

1. Agarwalla, M., & Sahu, T. N. (2024). Do human capital development and innovation matter in sustaining economic development? Panel data evidence from selected developing economies. *Sustainable Development, 32*(6), 6864-6880. https://doi.org/10.1002/sd.3059
2. Bayarcelik, E. B., & Taşel, F. (2012). Research and development: Source of economic growth. *Procedia-Social and Behavioral Sciences, 58,* 744-753. https://doi.org/10.1016/j.sbspro.2012.09.1052
3. Bilbao-Osorio, B., & Rodríguez-Pose, A. (2004). From R&D to innovation and economic growth in the EU. *Growth and Change, 35*(4), 434-455. https://doi.org/10.1111/j.1468-2257.2004.00256.x
4. Boeing, P., Eberle, J., & Howell, A. (2022). The impact of China's R&D subsidies on R&D investment, technological upgrading and economic growth. *Technological Forecasting and Social Change, 174,* 121212. https://doi.org/10.1016/j.techfore.2021.121212
5. Carillo, M. F. (2024). Human capital composition and long-run economic growth. *Economic Modelling, 137,* 106760. https://doi.org/10.1016/j.econmod.2024.106760
6. Chaabouni, S., & Mbarek, M. B. (2024). What will the impact of the COVID-19 pandemic be on human capital and economic growth? Evidence from the Eurozone. *Journal of the Knowledge Economy, 15*(1), 2482-2498. https://doi.org/10.1007/s13132-023-01328-3
7. Chan, D. K. (2012). *Capitalization of research and development expenditure in gross domestic product*. Census and Statistics Department, Hong Kong. Retrieved from https://www.statistics.gov.hk/wsc/CPS003-P1-S.pdf
8. Chan, K. L. P. (2022). Another wave of economic restructuring: Returns to R&D-investments: Evaluation of technological projects in Hong Kong. *HKU Theses Online (HKUTO)*. Retrieved from https://hub.hku.hk/handle/10722/328198
9. Chandra, K., Mansoor, A., & Sinha, K. B. (2018). The role of the state in promoting innovation efficacy: A comparative analysis of R&D spending and TFP growth in Hong Kong, Singapore, and Shenzhen. In *Conference Paper for the 17th International Schumpeter Society Conference*.
10. Che Sulaiman, N. F., Saputra, J., & Muhamad, S. (2021). Effects of human capital and innovation on economic growth in selected ASEAN countries: Evidence from panel regression approach. *The Journal of Asian Finance, Economics and Business, 8*(7), 43-54. https://doi.org/10.13106/jafeb.2021.vol8.no7.0043
11. Chen, Y., Wang, Y., Hu, D., & Zhou, Z. (2020). Government R&D subsidies, information

asymmetry, and the role of foreign investors: Evidence from a quasi-natural experiment on the Shanghai-Hong Kong stock connect. *Technological Forecasting and Social Change, 158,* 120162. https://doi.org/10.1016/j.techfore.2020.120162

12. Chu, A. C., & Cozzi, G. (2014). R&D and economic growth in a cash-in-advance economy. *International Economic Review, 55*(2), 507-524. https://doi.org/10.1111/iere.12059
13. Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica, 49*(4), 1057-1072. https://doi.org/10.2307/1912517
14. Dritsaki, M., & Dritsaki, C. (2023). R&D expenditures on innovation: A panel cointegration study of the EU countries. *Sustainability, 15,* 6637. https://doi.org/10.3390/su15086637
15. Edquist, H., & Henrekson, M. (2017). Swedish lessons: How important are ICT and R&D to economic growth? *Structural Change and Economic Dynamics, 42,* 1-12. https://doi.org/10.1016/j.strueco.2017.05.004
16. Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*(3), 424-438. https://doi.org/10.2307/1912791
17. Hanushek, E. A., & Woessmann, L. (2015). The economic impact of educational quality. In *Handbook of international development and education* (pp. 6-19). Edward Elgar Publishing. https://doi.org/10.4337/9781783473540.00009
18. Hasanov, R. I. (2023). Towards a sustainable future in aluminium production: environmental and economic benefits of revolutionary inert anode technology. *Journal of Sustainability Science and Management, 18*(10), 176-186. http://doi.org/10.46754/jssm.2023.10.012
19. Hasanov, R. I., & Safarli, A. J. (2023). New structural design for green supply chain management: The case of the aluminum industry. *New Design Ideas, 7*(2), 343-355. Retrieved from https://jomard-publishing.com/UploadFiles/Files/journals/NDI/V7N2/Hasanov_Safarli.pdf
20. HKIAS. (2023). *Continued increase in Hong Kong's gross expenditure on research and development in Hong Kong Innovation Activities Statistics 2022*. The Government of Hong Kong Special Administrative Region Press Release. Hong Kong Innovation Activities Statistics. Retrieved from https://www.info.gov.hk/gia/general/202312/21/P2023122100388.htm
21. Hong, J. P. (2017). Causal relationship between ICT R&D investment and economic growth in Korea. *Technological Forecasting and Social Change, 116,* 70-75. https://doi.org/10.1016/j.techfore.2016.11.005
22. Hu, B., Wang, L., & Yu, X. (2007). R&D and economic growth in China on the basis of data envelopment analysis: Evidence from Hebei Province, PRC. *Journal of Technology Management in China, 2*(3), 225-236. https://doi.org/10.1108/17468770710825160
23. Islam, H. (2025). Dynamic effects of uncertainty, risks, R&D, and innovation on global economic growth. *Innovation and Green Development, 4*(2), 100225. https://doi.org/10.1016/j.igd.2025.100225
24. ITB. (2023). *R&D activities of business sector in Hong Kong*. Information Technology and Broadcasting. Retrieved from https://www.legco.gov.hk/research-publications/english/2023issh06-RandD-activities-of-business-sector-in-hong-kong-20230503-e.pdf
25. Jalil, A., Rauf, A., & Han, L. (2024). Financial development, R&D and knowledge production: Empirical evidence from China. *Journal of the Knowledge Economy, 15*(3), 14617-14642. https://doi.org/10.1007/s13132-023-01675-1
26. Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control, 12,* 231-254. https://doi.org/10.1016/0165-1889(88)90041-3
27. Lai, A., & Maclean, R. (2011). Managing human capital in world cities: The development of Hong Kong into an education hub. *Asia Pacific Journal of Education, 31*(3), 249-262. https://doi.org/10.1080/02188791.2011.594418
28. Lu, H., Zhao, G., & Liu, S. (2024). Integrating circular economy and Industry 4.0 for sustainable supply chain management: a dynamic capability view. *Production Planning & Control, 35*(2), 170-186. https://doi.org/10.1080/09537287.2022.2063198
29. Lung, K.-L. (2012). Hong Kong and the knowledge-based economy: Developments and prospects. *Asian Education and Development Studies, 1*(3), 294-300. https://doi.org/10.1108/20463161211270509
30. Mabrouki, M. (2023). Patent, education, human capital, and economic growth in Scandinavian countries: A dynamic panel CS-ARDL analysis. *Journal of the Knowledge Economy, 14*(3), 3028-3043. https://doi.org/10.1007/s13132-022-01001-1
31. MacKinnon, J. G., Haug, A. A., & Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of applied Econometrics, 14*(5), 563-577. https://doi.org/10.1002/(SICI)1099-1255(199909/10)14:5<563::AID-JAE530>3.0.CO;2-R
32. Park, S. D. (2018). The nexus of FDI, R&D, and human capital on Chinese sustainable development: Evidence from a two-step approach. *Sustainability, 10*(6), 2063. https://doi.org/10.3390/su10062063
33. Pelinescu, E. (2015). The impact of human capital on economic growth. *Procedia Economics and Finance, 22,* 184-190. https://doi.org/10.1016/S2212-5671(15)00258-0
34. Pessoa, A. (2010). R&D and economic growth: How strong is the link? *Economics Letters, 107*(2), 152-154. https://doi.org/10.1016/j.econlet.2010.01.010
35. Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in

time series regression. *Biometrika, 75,* 335-346. https://doi.org/10.1093/biomet/75.2.335

36. Sharif, N., Chandra, K., Mansoor, A., & Sinha, K. B. (2021). A comparative analysis of research and development spending and total factor productivity growth in Hong Kong, Shenzhen, Singapore. *Structural Change and Economic Dynamics, 57,* 108-120. https://doi.org/10.1016/j.strueco.2021.02.004

37. Shi, S., Wu, S., & Yang, Z. (2024). Competitive advantages and the proximity of investment: Evidence from Hong Kong-listed real estate development firms in Mainland China. *Journal of Property Research, 41*(1), 1-22. https://doi.org/10.1080/09599916.2023.2279761

38. Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics, 66,* 225-250. https://doi.org/10.1016/0304-4076(94)01616-8

39. Tuna, K., Kayacan, E., & Bektaş, H. (2015). The relationship between research & development expenditures and economic growth: The case of Turkey. *Procedia – Social and Behavioral Sciences, 195,* 501-507. https://doi.org/10.1016/j.sbspro.2015.06.255

40. Tung, L. T., & Hoang, L. N. (2024). Impact of R&D expenditure on economic growth: Evidence from emerging economies. *Journal of Science and Technology Policy Management, 15*(3), 636-654. https://doi.org/10.1108/JSTPM-08-2022-0129

41. World Bank. (2024). *Data. Hong Kong SAR, China.* Retrieved from https://data.worldbank.org/country/hong-kong-sar-china