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# The Impact of Education and Human Capital on High-Tech Business Upgrading: Macro-level Evidence

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**Abstract**

In the contemporary digital economy, high-tech business upgrading is fundamentally constrained by the macroeconomic foundation of the national workforce. However, empirical studies often underestimate the impact of human capital, frequently yielding insignificant results. This study argues that such inconsistencies stem from methodological limitations, specifically the "inertia penalty," in which standard panel estimators over-penalize slow-moving structural variables, and the failure to account for cross-sectional dependence in global value chains. Using a comprehensive panel dataset covering 82 countries, this research examines the macro-level impact of education and human capital on high-tech business upgrading. To resolve the statistical puzzle, the study employs advanced econometric techniques—Feasible Generalized Least Squares (FGLS) and Fixed Effects with Driscoll-Kraay standard errors. The empirical results definitively confirm that when structural inertia and global interconnectedness are properly modeled, macro-level human capital is a powerful and highly significant driver of high-tech upgrading. Furthermore, the findings reveal that while human capital is a foundational driver, corporate research and development (R&D) serves as a critical parallel determinant for commercialization. This study contributes to the Macro-HRM and strategic management literature by proving the structural necessity of national education systems, while offering actionable insights for aligning public educational investments with corporate R&D incentives to foster industrial modernization.

**Keywords:** Macro-HRM; Human Capital; High-Tech Business Upgrading; Corporate R&D; Cross-Sectional Dependence; Driscoll-Kraay.

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## 1. Introduction

In the contemporary digital economy, high-tech business upgrading is a survival imperative for enterprises operating within highly competitive global value chains (GVCs). As firms transition toward data-driven systems, advanced manufacturing, and knowledge-intensive services, their success is strictly bounded by their capacity to absorb and commercialize new technologies (Colacchio & Vergori, 2022). Traditionally, strategic human resource management (HRM) has approached talent acquisition as a micro-level, firm-specific function. However, recent literature increasingly emphasizes that a firm's technological capability is fundamentally constrained by the macroeconomic environment—specifically, the aggregate quality of the national talent pool (Rehmani et al., 2021). This shift toward a Macro-HRM perspective argues that sustained corporate upgrading cannot be achieved through isolated firm-level hiring alone; rather, it requires a robust national foundation of human capital cultivated through systematic public education and training frameworks.

Despite the long-standing theoretical consensus that human capital is the primary engine of economic development and technological adoption (Benhabib & Spiegel, 1994), empirical macro-level studies analyzing the direct impact of human capital on high-tech business upgrading frequently yield conflicting or statistically insignificant results (Magida et al., 2025). This empirical puzzle stems from two distinct limitations in the existing literature. Methodologically, standard panel data estimators, such as conventional Fixed Effects models, heavily penalize "slow-moving" structural variables. Because national education levels exhibit high inertia and evolve gradually over decades, standard techniques often fail to capture their long-term structural impact, leading to misinterpretation of statistical attenuation as a lack of economic relevance (Tsai & Ho, 2025). Furthermore, these standard models frequently ignore cross-sectional dependence—the reality that in modern GVCs, high-tech upgrading in one nation is deeply interconnected with international trade and transnational knowledge spillovers (Alalmaee, 2025).

 

Theoretically, the literature often treats human capital as an automatic engine of innovation. This perspective overlooks a critical missing link: macro-level human capital is essentially a dormant asset. A highly educated workforce provides the necessary cognitive baseline, but it does not spontaneously generate commercialized high-tech outputs without an active strategic complementary asset (Jin & Liu, 2025). Corporate research and development (R&D) acts as this required mechanism, providing the infrastructure and strategic direction needed to convert latent educational potential into tangible business upgrading (Zhang & Yu, 2023).

This study aims to resolve these theoretical and methodological gaps by investigating the macro-level impact of education and human capital on high-tech business upgrading. Utilizing a comprehensive macro-level panel dataset, this research employs advanced econometric techniques—specifically, Feasible Generalized Least Squares and Fixed Effects with Driscoll-Kraay standard errors. These estimators are specifically selected to rigorously control for panel heteroskedasticity, temporal autocorrelation, and cross-sectional dependence, thereby correcting for biases that obscure the true impact of slowly moving structural variables.

The contributions of this paper are twofold. First, it advances Macro-HRM theory by empirically demonstrating that, when global interconnectedness and structural inertia are accurately modeled, macro-level human capital is a powerful, direct driver of high-tech upgrading. Second, it offers actionable insights for both corporate strategy and public policy, demonstrating that national educational investments must be complemented by active corporate R&D incentives to commercialize the workforce's capabilities effectively.

The remainder of this paper is organized as follows. Section 2 establishes the theoretical framework and reviews the relevant literature. Section 3 details the empirical methodology and dataset. Section 4 presents the advanced econometric results that resolve the Macro-HRM statistical puzzle. Finally, Section 5 concludes the study with strategic managerial implications and policy recommendations.

## 2. Literature Review

The theoretical boundary of human resource management has progressively expanded from firm-specific micro-processes to national-level frameworks, which are categorized in the literature as Macro-HRM (Rehmani et al., 2021). At this macroeconomic level, the national education system determines the aggregate baseline of skills, directly dictating the absorptive capacity of domestic enterprises. As classically posited by Nelson and Phelps (1966), education does not merely increase labor efficiency; it fundamentally enhances a nation's capacity to receive, decode, and implement new technologies. Education achieves this by equipping the workforce with foundational cognitive structures, enabling individuals to process complex, tacit knowledge and transfer it into organizational routines (Boon et al., 2018). In the contemporary digital economy, the rapid integration of advanced manufacturing, artificial intelligence, and data-driven systems fundamentally alters labor requirements. The core demand shifts aggressively from manual, routine-based execution toward non-routine cognitive and analytical problem-solving (Acemoglu & Restrepo, 2022). Consequently, national policies focusing on widespread digital literacy and advanced tertiary education are structural prerequisites for corporate modernization. For example, comprehensive policy frameworks that explicitly link digital infrastructure expansion with targeted human capital development are vital for improving labor productivity and enabling industrial upgrading across transitioning economies (World Bank, 2021). Building physical digital infrastructure—such as broadband networks or automated assembly lines—yields minimal economic returns if the domestic labor pool lacks the sophisticated analytical skills required to operate, maintain, and innovate upon these systems (Autor et al., 2022). Without this macro-level educational foundation, firm-level technological adoption remains structurally bottlenecked by severe talent shortages, rendering large-scale capital investments highly inefficient (Wang & Zhu, 2025).

While the strategic value of an educated workforce is well established, the macroeconomic literature consistently identifies national human capital as a "slow-moving" structural variable (Zeng et al., 2025). The accumulation of human capital involves prolonged gestation periods, characterized by significant temporal lags between the implementation of educational policies and the entry of highly skilled graduates into the labor market. Consider the life-cycle of national STEM (Science, Technology, Engineering, and Mathematics) initiatives: a policy designed to increase engineering capacities requires a minimum of four to six years to produce a single cohort of university graduates. Furthermore, post-graduation labor market frictions—such as search costs, geographical mobility constraints, and the time required for on-the-job training—create additional delays before these graduates fully integrate into the corporate sector and generate tangible technological outputs (Hanushek & Woessmann, 2021). Because of this inherent inertia, short-term fluctuations in educational spending or university enrollment rates do not trigger immediate shifts in national high-tech output (Magida et al., 2025; Lee & Lee,

 

2022). Theoretical models examining structural economic transitions emphasize that macro-human capital provides a stable, long-term baseline rather than a source of short-term volatility (Dong et al., 2025). Therefore, measuring the impact of education on high-tech upgrading requires methodologies capable of capturing delayed structural effects. Short-term observational windows and standard fixed-effects estimators—which primarily analyze within-country variance over short periods—often fail to register the deep, latent influence of educational maturation on corporate capability. These standard econometric models mistake macroeconomic lags for economic irrelevance, systematically attenuating the statistical significance of human capital variables (Tsai & Ho, 2025; Eberhardt & Teal, 2011).

Although a robust national talent pool is a necessary baseline condition for industrial upgrading, recent strategic management literature argues that human capital alone functions as a dormant macroeconomic asset (Jin & Liu, 2025). To translate latent educational potential into tangible technological advancement, firms must actively deploy strategic variables, predominantly through corporate research and development (R&D) investments (Zhang & Yu, 2023). The foundational concept of absorptive capacity, as originally established by Cohen and Levinthal (1990), highlights that external knowledge cannot be assimilated without internal cognitive structures, primarily developed through R&D. Recent literature extends this by formalizing a bidirectional complementarity between national talent and corporate strategy (Bouncken et al., 2022). On one hand, human capital requires the physical infrastructure, financial capital, and strategic orientation provided by corporate R&D environments to engage in applied innovation and knowledge creation. Without these R&D environments, highly educated workers are often underutilized, absorbed into administrative roles rather than technological commercialization (Ployhart et al., 2014).

On the other hand, corporate R&D expenditures become inefficient sunk costs if the available workforce lacks the cognitive capacity to execute complex research protocols or operate advanced diagnostic technologies. Thus, R&D and human capital are not substitutable inputs but strictly complementary forces. Recent empirical studies confirm this strong synergistic interaction, demonstrating that firm-level R&D intensity acts as the critical mechanism that activates and amplifies the economic utility of national human capital, actively converting academic knowledge into patented technologies and high-tech market outputs (Wu & Zeng, 2022; Dakhli & De Clercq, 2004).

Despite the established theoretical linkages between education, R&D, and corporate innovation, empirical evidence at the cross-national macro level remains fragmented. A primary limitation in the current literature is reliance on standard panel-data models that fail to account for the slow-moving nature of human capital and the reality of cross-sectional dependence (Shen et al., 2025). In the modern architecture of global value chains (GVCs), national economies do not operate as isolated, independent entities. High-tech business upgrading in one jurisdiction is heavily interconnected with neighboring and trading partner economies through transnational technological spillovers, intermediate goods trade networks, and foreign direct investment flows (Kano et al., 2020). Furthermore, industries integrated into GVCs are constantly subjected to shared macroeconomic shocks, such as global supply chain disruptions or international regulatory shifts. Standard estimators that assume cross-sectional independence generate biased, inconsistent coefficients by completely ignoring these spatial and economic network effects (Pesaran, 2021). Correcting for cross-sectional dependence is strictly vital for macro-level analysis; failing to do so assigns the variance caused by global economic integration to domestic variables, distorting the true causal impact of national education policies. By addressing these methodological gaps through advanced estimators capable of accurately correcting for both severe cross-sectional dependence and panel heteroskedasticity, this study posits the following hypotheses:

*H1: Macro-level human capital positively drives high-tech business upgrading, functioning as a foundational, long-term structural determinant characterized by high inertia.*

*H2: Corporate R&D intensity acts as a necessary complementary driver, actively driving the conversion of dormant macro-level human capital into commercialized high-tech business upgrading.*

## 3. Methodology

### *3.1. Data and Sample*

To empirically investigate the macro-level determinants of high-tech business upgrading, this study constructs a comprehensive macro-level panel dataset comprising 82 countries observed over a recent 14-year period. Due to variations in reporting cycles and statistical availability across different national contexts, the dataset is unbalanced, with 798 observations. The selection of these countries ensures a diverse representation of

 

economies participating in global value chains. Utilizing country-level aggregates is essential for this Macro-HRM and strategic management analysis, as it provides the necessary macroeconomic scale to evaluate how structural foundations—specifically national education systems—enable or constrain firm-level technological upgrading across borders (Rehmani et al., 2021).

### *3.2. Variables Measurement*

The empirical models rely on the following variables, all logarithmically transformed (with the exception of FDI) to reduce skewness and interpret coefficients as elasticities:

- Dependent Variable: High-Tech Business Upgrading (ln_MHT). This variable proxies the structural shift of the domestic corporate sector toward technology-intensive production and exports.
- Independent Variable: Human Capital (ln_HC). This serves as the primary variable of interest, measuring the aggregate cognitive capacity and educational attainment of the national workforce.
- Control Variables: To isolate the effect of human capital, the model incorporates a vector of macroeconomic and strategic control variables. Foreign Direct Investment (FDI) and Trade Openness (ln_Trade) capture external technological spillovers and the competitive pressures of global market integration. R&D Intensity (ln_RND) is included to measure the active corporate and national commitment to innovation, functioning as a critical indicator of absorptive capacity (Colacchio & Vergori, 2022). Physical Capital (ln_Capital) accounts for the fundamental infrastructure base required for industrial operations. Economic Development (ln_GDPpc) controls for the host nation's overall economic maturity and baseline purchasing power.

### *3.3. Econometric Strategy*

The econometric analysis begins by specifying a baseline panel data model to evaluate the relationship between human capital and high-tech upgrading. The standard structural equation is defined as follows:

$$ln\_MHT_{i,t} = \beta_0 + \beta_1 \ln\_HC_{i,t} + \beta_2 FDI_{i,t} + \beta_3 \ln_{RND_{i,t}} + \cdots + \mu_i + \varepsilon_{i,t}$$

where subscripts $i$ and $t$ denote the country and year, respectively. The term $\mu_i$ represents unobserved, time-invariant country-specific characteristics, and $\varepsilon_{i,t}$ denotes the idiosyncratic error term. To determine the appropriate baseline specification, a Hausman test is conducted. The test results consistently reject the null hypothesis of no correlation between the unique errors and the regressors, strictly justifying the use of the Fixed Effects (FE) specification over the Random Effects model.

However, relying solely on standard Fixed Effects models with cluster-robust standard errors introduces significant methodological limitations in this specific macro-HRM context. National human capital (ln_HC) is inherently a "slow-moving" structural variable characterized by high temporal inertia (Zeng et al., 2025). Standard FE estimators absorb most of the cross-sectional variance into the country-specific intercepts. Consequently, these models tend to over-penalize variables with high inertia, frequently masking the true long-term statistical significance of educational investments. Furthermore, standard panel models assume that cross-sectional units are independent. In the contemporary digital economy, high-tech business environments are highly globalized; economic shocks and technological upgrading in one country frequently spill over to trading partners through global value chains, resulting in severe cross-sectional dependence (Alalmaee, 2025).

To address these biases and assess the true statistical significance of human capital, this study shifts to two advanced panel estimators. First, the Feasible Generalized Least Squares estimator is applied. FGLS actively re-weights the data matrix, providing an efficient estimation that robustly handles panel-specific heteroskedasticity and first-order autoregressive AR(1) serial correlation (Alshubiri, 2025). Second, the study employs Fixed Effects regressions utilizing Driscoll-Kraay standard errors (Driscoll & Kraay, 1998). The Driscoll-Kraay non-parametric covariance matrix estimator yields standard errors that are simultaneously robust to heteroskedasticity, severe temporal autocorrelation, and spatial or cross-sectional dependence (Chand, 2026; Hoechle, 2007). By deploying both FGLS and Driscoll-Kraay estimators, the econometric strategy rigorously isolates the core impact of human capital from the complex statistical noise inherent in interconnected, globalized macroeconomic datasets.

 

## 4. Empirical Results

To establish the baseline intuition regarding the macroeconomic relationship between workforce education and technological advancement, Figure 1 illustrates the raw correlation across the sampled countries. The scatter plot, fitted with a linear regression line, demonstrates a clear positive association between the log of human capital (ln_HC) and the log of high-tech business upgrading (ln_MHT). This initial visualization confirms the foundational assumption of Macro-HRM theory: economies with higher aggregate levels of educational attainment tend to exhibit greater structural capacity for high-tech industrial output. However, while this raw correlation is indicative, it does not account for temporal dynamics, country-specific unobserved heterogeneity, or the complex interconnectedness of global markets, which necessitate rigorous panel-data estimation.

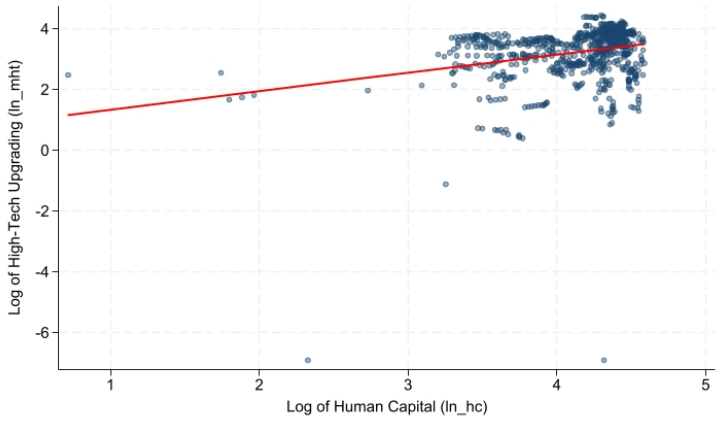


Figure 1. Correlation between Macro-level Human Capital and High-Tech Upgrading

Table 1 presents the results of the econometric modeling across the unbalanced panel of 82 countries (798 observations). Column 1 reports the baseline Fixed Effects (FE) specification utilizing cluster-robust standard errors.

Table 1. Panel Data Estimation Results

| Variables | (1) Fixed Effects (Robust) | (2) FGLS (Hetero & AR1) | (3) Fixed Effects (Driscoll-Kraay) |
|---|---|---|---|
| Human Capital (ln_ HC) | 0.888 | 0.137*** | 0.888*** |
| | (0.624) | (0.045) | (0.277) |
| Foreign Direct Investment (FDI) | 0.001 | -0.0001 | 0.001 |
| | (0.001) | (0.0001) | (0.000) |
| R&D Intensity (ln_ RND) | 0.085 | 0.345*** | 0.085** |
| | (0.134) | (0.022) | (0.042) |
| Physical Capital (ln_Capital) | -0.471 | 0.017 | -0.471*** |
| | (0.285) | (0.045) | (0.151) |
| Trade Openness (ln_Trade) | 0.272* | -0.047* | 0.272** |
| | (0.156) | (0.025) | (0.116) |
| Economic Development (ln_GDPpc) | -0.354 | 0.049 | -0.354** |
| | (0.338) | (0.041) | (0.131) |
| Constant | 3.484 | 2.437*** | 3.484** |
| | (4.480) | (0.419) | (1.211) |
| **Model Diagnostics** | | | |
| Observations | 798 | 792 | 798 |
| Number of Countries | 82 | 76 | 82 |

 

*Note. Standard errors are adjusted according to the respective estimator. ***, **, and * denote significance at the 1%, 5%, and 10% levels.*

In the standard FE model (Column 1), the coefficient for human capital (ln_HC) is positive but fails to reach statistical significance (p = 0.158). From a methodological standpoint, this insignificance is not a reflection of economic irrelevance, but rather an artifact of the "inertia penalty" inherent to standard FE estimators. Standard FE models apply a within-transformation that relies exclusively on time-series variance. Because macro-level human capital possesses high temporal inertia, its within-country variance is minimal. Consequently, the FE estimator absorbs the majority of this slow-moving structural effect into the time-invariant country-specific intercepts ($\mu_i$), inducing severe attenuation bias and statistically masking its long-term impact.

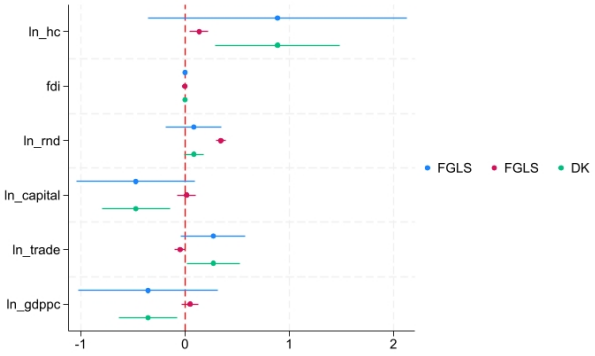


Figure 2. Comparison of Estimated Coefficients Across Baseline and Advanced Estimators

To overcome the methodological limitations of the baseline model, Columns 2 and 3 of Table 1, alongside the visual evidence in Figure 2, present the results from the advanced estimators. Figure 2 provides a direct coefficient comparison across the FE, FGLS, and DK models, visually demonstrating how the advanced techniques isolate the true statistical significance of the independent variables.

When controlling for panel-specific heteroskedasticity and temporal autocorrelation using Feasible Generalized Least Squares (Table 1, Column 2), the impact of human capital becomes highly significant (coefficient = 0.137, p = 0.002). Furthermore, the Fixed Effects model with Driscoll-Kraay standard errors (Table 1, Column 3) explicitly corrects for cross-sectional dependence—a critical requirement given the interconnected nature of global value chains where technological shocks routinely spill over across borders (Driscoll & Kraay, 1998; Hoechle, 2007). Under the Driscoll-Kraay specification, human capital emerges as a powerful and highly significant driver of high-tech upgrading (coefficient = 0.888, p = 0.007). As Figure 2 visually confirms, while the confidence interval for ln_HC under standard FE assumptions crosses the zero line, the FGLS and DK estimates are distinctly positive and bounded away from zero. By properly accounting for structural inertia and global interconnectedness, these advanced estimators resolve the statistical puzzle and confirm the foundational role of macro-level education.

Beyond the baseline of human capital, the empirical results consistently highlight the critical role of corporate research and development (ln_RND). In both the FGLS and Driscoll-Kraay specifications, R&D intensity maintains a positive, statistically significant coefficient. This finding substantiates the theoretical premise that human capital alone functions as a dormant macroeconomic asset. While a highly educated national workforce provides the necessary cognitive boundaries and absorptive capacity for a country, it requires an active strategic complementary asset to be commercialized into tangible technological outputs. Corporate R&D investments provide this exact mechanism, creating the infrastructure and strategic direction that activate the educated talent pool. Consequently, the empirical evidence demonstrates a clear dual-pillar dynamic: macro-level education supplies the foundational talent, while active corporate R&D drives the actual transition toward high-tech business upgrading.

## 5. Conclusions and Recommendations

This study empirically resolves a critical statistical and theoretical puzzle within the Macro-HRM and strategic management literature regarding the true driver of high-tech business upgrading. Standard panel-data models often fail to capture the importance of national human capital because they strictly penalize structural

 

macroeconomic variables with high temporal inertia. By deploying advanced econometric estimators—specifically Feasible Generalized Least Squares and Fixed Effects with Driscoll-Kraay standard errors—on a comprehensive global panel dataset, this research actively corrects for both structural inertia and the severe cross-sectional dependence inherent in interconnected global value chains.

The empirical findings provide definitive evidence that macro-level human capital is a robust, positive, and foundational driver of high-tech business upgrading. Furthermore, the results mathematically confirm that human capital requires an active strategic mechanism to be fully commercialized; corporate R&D intensity serves as this essential complementary driver, acting as a complementary foundational pillar alongside the educated workforce to transition domestic business sectors toward high-tech outputs.

The definitive statistical significance of human capital sends a clear, actionable directive to corporate executives and strategic HR managers: enterprises cannot simply "import" or purchase high-tech capabilities through raw physical capital or foreign direct investment. The cognitive and absorptive capacity of the available workforce fundamentally gates the structural upgrading of a firm's business model. Therefore, corporate strategy must shift away from viewing talent acquisition strictly as a micro-level operational task. Instead, firms must align their strategic expansion plans with the macroeconomic realities of the host country's educational outputs. To avoid leaving human capital as a dormant asset, executives must aggressively invest in internal corporate R&D infrastructure, ensuring that highly educated employees have the environment and resources to drive technological commercialization actively.

From a macroeconomic management perspective, the findings underscore that public education funding is the ultimate structural investment for national industrial competitiveness. Short-term economic stimulus packages cannot substitute for the long-term, slow-moving accumulation of a highly educated talent pool. However, because the complementarity between human capital and R&D is strictly evident, public policymakers must adopt a dual-pillar strategy. Governments should not only focus on expanding tertiary education and digital literacy programs but also actively foster national innovation ecosystems where domestic businesses are financially incentivized to invest in R&D. This cohesive approach ensures that the educated workforce is efficiently absorbed by the domestic corporate sector, directly translating public educational investments into high-tech economic growth.

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**References**

Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in US wage inequality. *Econometrica*, *90*(5), 1973–2016. https://doi.org/10.3982/ECTA19815

Alalmaee, H. (2025). Sustainability through policy stringency: Analysing the impact on financial development. *Sustainability*, *17*(4), 1374. https://doi.org/10.3390/su17041374

Alshubiri, F. (2025). Governance quality systems and operations of sustainable smart cities. *European Journal of Management Studies*, *30*(1), 1-25. https://doi.org/10.1108/EJMS-11-2025-0210

Autor, D., Mindell, D. A., & Reynolds, E. B. (2022). *The work of the future: Building better jobs in an age of intelligent machines*. MIT Press. https://doi.org/10.7551/mitpress/14109.001.0001

Benhabib, J., & Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary Economics*, *34*(2), 143-173. https://doi.org/10.1016/0304-3932(94)90047-7

Boon, C., Eckardt, R., Lepak, D. P., & Boselie, P. (2018). Integrating strategic human capital and strategic human resource management. *The International Journal of Human Resource Management*, *29*(1), 34–67. https://doi.org/10.1080/09585192.2017.1380063

Bouncken, R. B., Kraus, S., & Roig-Tierno, N. (2022). Knowledge- and innovation-based business models for future growth: Digitalized business models and portfolio considerations. *Review of Managerial Science*, *16*(1), 1–14. https://doi.org/10.1007/s11846-019-00366-z

 

Chand, S. A. (2026). Leveraging Digital Banking to Enhance Financial Inclusion in Small Island Developing States: A Study of Fiji. *Journal of Risk and Financial Management*, *19*(2), 158. https://doi.org/10.3390/jrfm19020158

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128-152. https://doi.org/10.2307/2393553

Colacchio, G., & Vergori, A. S. (2022). GDP growth rate, tourism expansion and labor market dynamics: Applied research focused on the Italian economy. *National Accounting Review*, *4*(3), 310–328. https://doi.org/10.3934/nar.2022018

Dakhli, M., & De Clercq, D. (2004). Human capital, social capital, and innovation: A multi-country study. *Entrepreneurship & Regional Development*, *16*(2), 107–128. https://doi.org/10.1080/0898562041000167783 5

Dong, R., Shen, S., & Yang, Y. (2025). Evolution Characteristics and Driving Mechanisms of Innovation's Spatial Pattern in Beijing–Tianjin–Hebei Urban Agglomeration Under Coordinated Development Policy: Evidence from Patent Data. *Land*, *14*(11), 2206. https://doi.org/10.3390/land14112206

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, *80*(4), 549-560. https://doi.org/10.1162/003465398557825

Eberhardt, M., & Teal, F. (2011). Econometrics for grumblers: A new look at the literature on cross-country growth empirics. *Journal of Economic Surveys*, *25*(1), 109–155. https://doi.org/10.1111/j.1467-6419.2010.00624.x

Hanushek, E. A., & Woessmann, L. (2021). Education and economic growth. *Oxford Research Encyclopedia of Economics and Finance*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190625979.013.651

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, *7*(3), 281-312. https://doi.org/10.1177/1536867X0700700301

Jin, Y., & Liu, B. (2025). Industry concentration and digital process innovation: Evidence from Chinese rail transit firms. *Sustainability*, *17*(9), 4116. https://doi.org/10.3390/su17094116

Kano, L., Tsang, E. W. K., & Yeung, H. W. C. (2020). Global value chains: A review of the multi-disciplinary literature. *Journal of International Business Studies*, *51*(4), 577–622. https://doi.org/10.1057/s41267-020-00304-2

Lee, J. W., & Lee, H. (2022). Human capital and economic growth: A cross-country analysis. *Journal of Macroeconomics*, *72*, 103408. https://doi.org/10.1016/j.jmacro.2021.103408

Magida, N., Ncanywa, T., Sibanda, K., & Asaleye, A. J. (2025). Human Capital Development and Public Health Expenditure: Assessing the Long-Term Sustainability of Economic Development Models. *Social Sciences*, *14*(6), 351. https://doi.org/10.3390/socsci14060351

Nelson, R. R., & Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, *56*(1/2), 69-75. http://www.jstor.org/stable/1821269

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, *60*(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7

Ployhart, R. E., Nyberg, A. J., Reilly, G., & Maltarich, M. A. (2014). Human capital is dead; long live human capital resources! *Journal of Management*, *40*(2), 371–398. https://doi.org/10.1177/0149206313512152

Rehmani, K., Yasir, A., Afshan, N., Hussain, T., & Raza, M. (2021). Theoretic insights on the concept of internal fit of HR elements within the construct of high performance work system. *Production & Manufacturing Research*, *9*(1), 81–102. https://doi.org/10.1080/21693277.2021.1956380

Shen, W., Zhong, S., & Yang, X. (2025). The effects of digitalization on the quality of marine economic development: evidence from a micro-level perspective. *Frontiers in Marine Science*, *12*, 1587019. https://doi.org/10.3389/fmars.2025.1587019

Tsai, J. C., & Ho, C. W. (2025). Impact of Digital Economy on Energy Consumption and Energy Efficiency. *Sustainability*, *17*(23), 10831. https://doi.org/10.3390/su172310831

Wang, H., & Zhu, L. (2025). Technological Innovation, Industrial Structure Upgrading, and the Coordinated Development of Regional Economies. *Sustainability*, *17*(17), 7880. https://doi.org/10.3390/su17177880

 

World Bank. (2021). *Digital government transformation in Vietnam: Global lessons and policy implications*. Washington, DC: The World Bank. https://doi.org/10.1596/37179

Wu, X., & Zeng, S. (2022). R&D investment, internal control and enterprise performance—An empirical study based on the listed companies in China of the core industry of the digital economy. *Sustainability*, *14*(24), 16700. https://doi.org/10.3390/su142416700

Zeng, S., Ding, Y., Fu, C., Lv, W., & Yu, F. (2025). An Empirical Investigation on How Population Aging Affects Economic Development: A Panel Data Analysis of 16 Prefecture-Level Cities in Anhui, China. *Sustainability*, *17*(14), 6578. https://doi.org/10.3390/su17146578

Zhang, X., & Yu, B. (2023). The impact of ownership structure on technological innovation and energy intensity: Evidence from China. *Sustainability*, *15*(11), 8512. https://doi.org/10.3390/su15118512