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Review

EDUCATIONAL EFFICIENCY AND TECHNOLOGY SKILL DEVELOPMENT: A CROSS-INCOME COUNTRY ANALYSIS

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Abstract. The relationship between educational efficiency, technology proficiency, and economic development remains a subject of debate, with existing empirical studies producing mixed results. Our study aims to clarify this association by investigating how advancements in technology skills can enhance educational outcomes and, in turn, stimulate economic growth. We employ a dynamic panel model with fixed effects, utilizing data from 2009 to 2022 that covers 23 lower-income, 23 middle-income, and 18 higher-income countries. Our findings reveal a significant positive impact of educational efficiency and technology proficiency on economic development, particularly in low-income countries, where the synergy between these factors drives accelerated growth. In higher-income countries, the influence of educational efficiency appears minimal, but the persistent benefits of technological competencies emphasize the critical role of technology in sustaining economic progress. Robustness checks affirm the strength of these results, leading to actionable policy recommendations that prioritize investments in education and technology to foster sustainable economic development across diverse income groups.

Keywords: SDG 4, economic development, educational efficiency, technology proficiency.

JEL Classification: O32.

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1. Introduction

Learning and competency acquisition are recognized as crucial channels of economic progress in both academic and practical realms. This understanding has led to substantial investments in human capital to foster economic development. While significant advancements have been made in analyzing the connection between learning, competencies, and economic development, there is still ample opportunity for further innovation. Key areas such as model design, measurement methods for learning acquisition and competencies, and the application of robustness tests offer room for additional progress.

Although there is a prevailing belief that investing in human resources is vital in driving economic expansion, quantitative evidence often presents mixed results. These inconclusive findings, particularly regarding the role of educational efficiency and technological competencies in promoting economic development, present challenges for policymakers (Jie, 2016; Das, 2019). Both empirical and theoretical studies of the association of educational efficiency and technology skills with economic growth reveal several important concerns. First, variations in how learning and competencies are measured and differences in economic growth metrics add complexity to these studies. Second, the choice of countries analyzed introduces additional variability, as lower-income and higher-income nations often experience different outcomes. Finally, diverse estimation methods can yield varying results, emphasizing the need for systematic categorization based on methodological approaches.

This study enriches the academic literature by addressing the issues mentioned above. Our focus is on educational efficiency rather than the quantity of learning, as research suggests that efficiency significantly affects economic growth (Hanushek & Kimko, 2000; Barro, 2001). Sustainable Development Goal 4 (SDG 4) from the United Nations (n.d.) is utilized in our research to address challenges in measuring educational efficiency. Such an objective emphasizes the need to "ensure inclusive and equitable quality education and promote lifelong learning opportunities for all". Notably, our approach uses indicator 4.7.1 from SDG 4 to create a metric for educational efficiency.

Unlike previous studies, we concentrate on a specific skill-technology competence – rather than employing a more expansive definition of competencies. Educational advancements are becoming more closely associated with the enhancement of technological abilities among both students and teachers. This link suggests that technological skills may directly influence the effectiveness of education. Torrato et al. (2020) underscore the need for more research on the growth effects of interaction terms within regression models. They point out that the lack of studies utilizing these variables hinders a complete understanding of how learning investments and competencies promote economic progress. This study explores the synergy between technology proficiency and educational effectiveness to evaluate their contribution to economic expansion. An ongoing challenge in the literature is the issue of endogeneity, highlighted by Hanushek and Wößmann (2007), Lee (2001), and Cabardo et al. (2014). This concern often emerges in growth analyses due to the reciprocal nature of educational efficiency, technology skills, and economic progress, leading to biased coefficients. We employ the GMM technique to address this issue.

Our methodology builds on an endogenous growth framework, modified to include educational efficiency and technology competence as key components. The primary goal is to quantify the individual impacts of these variables, as laid out by SDG 4, on economic progress. Moreover, we assess how these factors interact to shape overall economic growth. The analysis spans two distinct time frames to account for potential technological and educational dynamics shifts. Additionally, we divide countries into different income categories – low, middle, and high – to examine if the results are consistent across varying economic environments.

The study finds a favorable effect of technology proficiency and educational efficiency on economic development across all income groups. However, the impact of educational efficiency is more pronounced than technology proficiency alone, as reflected in a more substantial coefficient for educational efficiency. The interaction between technology proficiency and educational efficiency shows an even more significant positive influence on economic development, indicating that technology proficiency enhances educational efficiency's effectiveness. This combined effect is important in low-income countries, where it drives substantial economic progress and supports continued growth in middle- and high-income nations by improving workforce skills. The study also reveals that the impact of these factors is stronger from 2016 to 2023 compared to 2010 to 2015, likely due to advancements in digital technology. Additionally, when analyzing countries by income levels, the combined effect of technology proficiency and educational efficiency shows more substantial coefficients in low-income countries, highlighting their potential for growth through improvements in education and technology. This finding challenges earlier studies that showed minimal impacts of human capital investment in such economies.

This paper is structured into several Sections. Section 2 comprehensively reviews the literature on educational efficiency, technology proficiency, and their relationship with economic growth. Section 3 details the data sources and variables utilized in the analysis. Section 4 describes the empirical methodology. The findings and their policy implications are discussed in Section 5. Section 6 presents the results of robustness checks to ensure the reliability of the analysis, while Section 7 concludes the paper with a summary of key insights and recommendations.

2. Review of the literature

The evolution of endogenous growth frameworks has significantly contributed to understanding the elements that influence sustained economic expansion. These models highlight the critical role of educational efficiency and technological capabilities, often classified under the broader term of human capital, in driving economic advancement (Shaharuddin et al., 2022; Hero, 2020; and Permani, 2009). These models delve into the various pathways and dynamics through which education and skill development influence economic outcomes. A significant body of research points to the indirect contributions of human capital, mainly through externalities that emerge from enhanced learning and skills acquisition (Nelson & Phelps, 1966). These externalities often materialize when human capital is integrated into production, boosting labor efficiency, stimulating innovation, and facilitating technological progress. Figure 1 provides a visual representation of these interactions, capturing the indirect contributions of human capital to economic growth while referencing key studies in this area.

There are four key ways in which educational efficiency and technological proficiency drive economic development. First, human capital is crucial in enhancing labor productivity (Jain et al., 2022). Second, human capital positively influences labor market participation, where education boosts job prospects and workforce engagement (Glewwe, 2002; Klasen, 2002). Third, human capital and investment are interconnected, with a well-educated workforce able to use capital more effectively (Matsa, 2018). Fourth, income supports human capital growth, spurring innovation and product diversification that fuel economic progress (Hummels & Klenow, 2005; Romer, 1990).

The body of research on educational efficiency and technological proficiency's role in economic progress falls into two broad categories. The first focuses on educational efficiency. For example, Barro (2001) showed that both the level and quality of learning contribute to economic growth, with educational quality having a more pronounced effect. Similarly, Hanushek and Kimko (2000) found that education quality substantially impacts growth more than the number of schooling years.

The second category explores the joint influence of learning and competencies. Dedrick et al. (2003) stressed cognitive skills' significant role in earnings, income distribution, and economic growth. They uncovered large competency shortcomings in emerging economies and advocated for educational reforms to bridge these divides, although they also acknowledged the challenge of measuring school quality across nations.

A detailed review by Hawkes and Ugur (2012) of 33 empirical studies reinforced the positive connection between learning, competencies, and economic development. However, they emphasized the complexities in defining and measuring education and skills, which are critical for policymakers aiming to enhance economic performance. Their review underscored the vital need to invest in human capital to drive economic development, mainly through metrics like teacher-student ratios and teacher qualifications (Islam et al., 2024).

Single-country studies offer valuable insights into the impact of educational efficiency and technological proficiency on economic development by considering specific contextual factors. For instance, Hulten (2018) analyzed the U.S. economy, noting the transformative effects of technological advancements and globalization on economic structures. His research emphasized developing diverse skills and competencies to sustain growth. Similarly, Stankić et al. (2018) studied Serbia's educational system and its response to technological changes, finding that education and digital technology are crucial for social and country progress. Bilan et al. (2023) investigated digital technology trends across EU countries, using correlation regression to evaluate its impact on the Global Knowledge Index (GKI), and identified key factors that drive knowledge-based economies.

Jouali et al. (2024) examined the association of digital technology and economic growth in Morocco with the ARDL model, revealing that while internet access had minimal direct effects on growth, investments in research, development, and higher education significantly contributed to economic expansion. Additional research on telecommunications infrastructure has highlighted its role in enhancing educational outcomes. Jiménez et al. (2014) assessed the

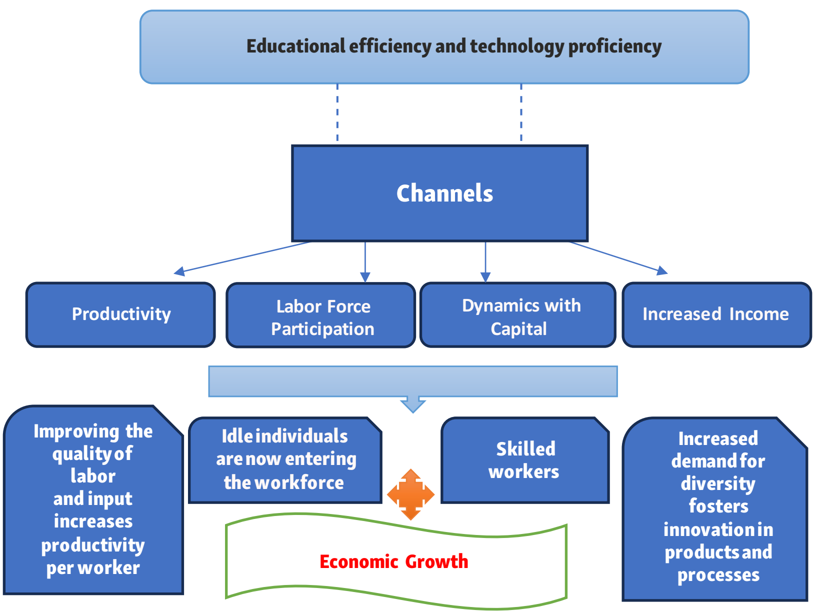

Figure 1. Educational efficiency and technology proficiency affect economic growth

effect of Digital communication investments on economic development in 45 African economies, finding that internet usage was beneficial where educational access was improved, although mobile phone usage had less impact. Sahlberg (2006) examined how internet access affects educational inequality, concluding that it has a more notable effect on reducing disparities in high-income economies than in middle-income ones.

3. Datasets and key variables

The primary factors affecting economic development are identified in traditional economic growth theory, which offers a robust framework for analyzing economic development. Our model integrates several essential economic performance elements based on Barro's (2001) methodology. These include government consumption (CONS), which represents public spending's influence on economic activity; institutional quality (IQ), reflecting the effectiveness of governance and institutions; and physical infrastructure (PI), which affects productivity and operational efficiency.

Additionally, our model incorporates the inflation rate (INF), which can influence economic stability and growth dynamics. It also considers global investment (INV) and foreign direct investment (FDI), crucial for capital formation and technological progress. The fertility rate (FERT) is included to account for its effect on labor market dynamics and long-term economic growth potential. This comprehensive approach provides a detailed understanding of the factors driving GDP growth and their relative impacts on economic performance.

A central issue concerns the selection of indicators for measuring learning outcomes and competencies, often determined by the availability of data rather than their suitability for guiding regulatory decisions. Frequently used human capital indicators tend to focus on inputs to the educational process, such as enrollment rates, which reflect costs but fail to capture actual learning outcomes. Therefore, a productive discussion among scholars and policymakers on the definition and measurement of learning and competencies could enhance the effectiveness of academic contributions to policy decisions in this domain.

Our research develops variables for technology proficiency and educational efficiency, guided by the SDG 4 of the United Nations (n.d.), which aims to promote comprehensive and fair learning opportunities. We employ SDG Indicator 4.4.1 to assess technology proficiency, which tracks the percentage of young people and adults possessing technology competencies. This data is obtained from several repositories, as detailed in Appendix Table A2.

For educational efficiency, we apply SDG Indicator 4.7.1, which monitors the inclusion of social involvement and enduring learning in domestic strategies, teacher training, curricula, and student assessments. The data are sourced from UNESCO, national education ministries, and local statistical agencies.

We created an aggregated indice to assess educational efficiency (EDU), rated from 0 (low quality) to 4 (high quality), based on four components: Teacher Education (TE), Student Assessment (SA), Curricula (CURR), and National Education Policies (NEP). Each element is rated according to national progress in these areas, with NEP measuring the alignment of policies with educational goals, CURR reflecting the incorporation of main citizenship concepts, TE assessing the quality of teacher preparation, and SA evaluating how well student assessments meet international standards.

The study utilizes a dynamic panel with fixed effects, analyzing data from 2009 to 2022 across 64 countries. These include 23 lower-income, 23 middle-income, and 18 higher-income countries, allowing for a comprehensive exploration of economic trends and policy impacts across varying income levels. By incorporating fixed effects, the study controls for time-invariant country-specific factors, providing robust insights into how different income groups respond to global economic dynamics, policy interventions, and external shocks over time. The analysis period captures significant technological and economic transformations, offering insights into the varying impacts of education and technology across countries. Detailed lists of countries, the description of the variables, and the summary statistics are provided in Appendix Tables A1, Table A2–A3, respectively.

4. Empirical methodology

Our study builds on key research in economic development, particularly the works of Nelson, 1964; Mankiw et al., 1992 and Lau et al., 1991). We employ a similar approach to Lau et al. (1991), who expanded an endogenous growth model within a classical theoretical framework. Their model integrates critical variables and mechanisms that help explain sustained economic growth. This framework enables us to examine how different elements influence growth, providing a deeper insight into the factors that drive long-term economic development.

$$Dy = F(y, y^*), \tag{1}$$

where Dy is the output per capita growth rate, y^* the sustained level of output per capita, and y the actual level of output per capita. In modifying the Lau et al. (1991) model, we introduce two critical variables: educational efficiency and technology proficiency, which act as proxies for human capital accumulation. Initially, these variables are treated separately to evaluate their contributions. Recent studies, such as Das (2019), suggest that advancements in technology proficiency – particularly among students and teachers – may directly link to educational efficiency. Hawkes and Ugur (2012) emphasize the importance of including interaction terms in growth models to capture the combined effects of multiple variables, yet few studies have examined these interactions.

Our analysis proceeds in two stages to address this gap. First, we assess the independent impacts of educational efficiency and technology proficiency. Next, we explore the interaction between these two variables to evaluate their joint effect on economic development. Based on Equation (1), the model's extended form incorporates these interaction terms to offer deeper insights into the evolving interplay between the advancement of human capital and economic development.

$$\begin{aligned} GDP\_growth_{i,t} &= \alpha_0 + \beta_1 GDP\_growth_{i,t-1} + \beta_2 EDU_{i,t} + \beta_3 ICT_{i,t} + \\ &\beta_4 EDU_{i,t} \times ICT_{i,t} + X_{i,t} + \delta_i + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

In this model, $GDP\_growth_{i,t-1}$ reflects the short-term autoregressive behavior of $GDP\_growth_{i,t}$. The variable EDU measures educational efficiency, while ICT captures technological skill acquisition. The vector X includes common explanatory variables in economic growth models, such as government consumption (CONS), institutional quality (IQ), infrastructure (PI), inflation (INF), fertility rate (FERT), investment (INV), and foreign direct investment (FDI). δ accounts for country-specific effects, and ϵ_{it} represents the error term.

However, estimating models like Equation (2) pose challenges, mainly due to the possible endogeneity of key variables, such as educational efficiency, which may be influenced by GDP growth. If this issue is not addressed, reverse causality can lead to biased estimates. When incorporating human capital into these models, the endogeneity issue surfaces due to the intertwined nature of education and economic growth: improved education can drive growth, and higher growth can further enhance educational outcomes. This reciprocal relationship can create a ”virtuous cycle,” potentially inflating the assessed effect of human capital on economic growth.

In addition, we explore the effects of shocks to educational efficiency and technology proficiency on economic development according to income categories. High educational efficiency improves workforce skills, productivity, and innovation, while technology proficiency is crucial for national competitiveness. Understanding how these shocks impact economic development reveals crucial insights into the flexibility and endurance of workforce and identifies factors that either support or hinder economic growth.

We ran the Arellano-Bond tests to assess autocorrelation and utilized the Hansen test to ensure the exogeneity of the instruments. The results in Appendix Table A5 indicated significant first-order autocorrelation in the residuals, a common occurrence in dynamic panel data models (Arellano & Bond, 1991). However, no significant second-order autocorrelation was observed, suggesting that the model specification effectively captured the dynamic relationships. Additionally, the Hansen test produced a p-value above the 5% significance level, leading us to accept the null hypothesis and indicating no significant endogeneity concern. Despite challenges such as autocorrelation and endogeneity, GMM provides reliable estimates by handling these issues effectively. First-order autocorrelation is addressed through the efficient moment conditions used in the Arellano-Bond estimator, and GMM ensures consistent and asymptotically efficient estimates. We also conducted unit root tests (ADF and PP) to examine the consistency of the data over time. As indicated in Appendix Table A4, all variables except. The GDP growth rates were unstable in their original form but became stable after taking the first difference. Consequently, we use the first differences of all variables in our empirical analysis.

5. Results of the empirical regressions

Appendix Table A5 summarizes the estimates of our regression. In column (1), we only use the technology proficiency variable. In the subsequent step, we add the educational efficiency variable (column 2), and in the final step, we include the interaction term between technology proficiency and educational efficiency (columns 3, 4, and 5).

The findings reveal a favorable effect of technology proficiency and educational efficiency on economic development, highlighting the beneficial impact of these factors across all country categories. Notably, its impact is less pronounced when technology proficiency is considered alone than when educational efficiency is introduced. Additionally, educational efficiency favors global development more than technology proficiency, as evidenced by a stronger coefficient for the educational efficiency variable (column 2).

The interaction term "ICT x EDU" provides a significant insight from this study, demonstrating a notably greater positive impact on economic development (column 3). The coefficient for this interaction term is 0.039, surpassing the standalone effects of technology proficiency and educational efficiency (columns 1 and 2). This indicates that advancements in technology proficiency enhance the effectiveness of educational efficiency, thereby boosting economic development.

For policymakers, these results highlight the importance of investing in both digital technology and educational efficiency. In low-income countries, this combined approach can drive substantial economic progress. It supports sustained growth in middle- and high-income countries by improving workforce skills and aligning educational practices with technological advancements.

In a further analysis, we examined the data across two separate time frames: 2010–2015, detailed in column 4, and 2016–2023, outlined in column 5, reveals that the impact of technology proficiency and educational efficiency on economic development is more pronounced in the latter period. This increased influence is likely due to significant advancements in digital technology, which have improved educational efficiency and contributed to better economic outcomes.

In the subsequent part of our study, we analyze how our key variables influence countries based on their income levels. Appendix Table A6 presents the regression results, categorizing countries as low-income in the first column, middle-income in the second column, and high-income in the third column. The findings indicate that technology proficiency, educational efficiency, and combined effects exhibit stronger coefficients in low-income countries. While this result seems surprising since poor economies generally have less advanced technology and education systems, it underscores the significant growth potential in these areas within such countries, which can lead to a more pronounced impact on economic development. Our results for low-income nations differ from some research by Manu and Mensah (2015), which found minimal impacts of human capital investment on economic growth. These studies suggested that more detailed measures of human capital could reveal greater effects, which is consistent with our results and supports economic theory.

6. Discussion and interpretation of results

Our study reveals the advantageous effects of technology proficiency and educational efficiency on economic development, supporting the findings of earlier research, such as Soyemi and Soyemi (2020), which emphasize the role of cognitive skills in driving economic progress. A novel aspect of our study is identifying a synergistic relationship between technology proficiency and educational efficiency. We demonstrate that high educational efficiency substantially boost the positive effects of technology proficiency. This synergy highlights the combined impact of these factors on promoting economic growth.

We have observed a stronger effect of technology proficiency and educational efficiency on economic development in recent years compared to earlier periods. This can be attributed to significant advancements in digital technology, which have improved educational efficiency and boosted economic development outcomes (Chen & Price, 2006). Our study also addresses concerns from Hawkes and Ugur (2012) regarding measurement issues by utilizing indicators from the United Nations' (n.d.) SDG 4 to gauge educational efficiency.

Data across different income levels reveals that technology proficiency and educational efficiency have a more pronounced impact in low-income countries than their middle- and high-income counterparts. While this may seem unexpected, given that low-income countries often struggle with technology and education, it highlights their substantial potential for improvement. Enhancements in these areas can significantly drive economic growth in such nations. Our findings align with studies by Bilan et al. (2023) and Jouali et al. (2024), which investigate the relationships between digital technology, the knowledge economy, and economic development. Our research provides a fresh perspective by analyzing these variables across various income levels, showing powerful effects in low-income countries.

The policy implications are notable. Investing in technology and education is essential, and policymakers should design strategies that integrate technological progress with educational advancements to maximize their combined impact. Our research emphasizes the need for flexible policies that adapt to technological changes, especially given the more significant effects observed recently.

The more substantial impacts of technology proficiency and educational efficiency in low-income countries suggest considerable growth potential through improvements in these areas. Policymakers should implement targeted strategies to bridge the digital and educational gaps, with support from developed nations and international organizations, to promote technology transfer and knowledge sharing.

The increase in the impact of technology proficiency and educational efficiency from 2016 to 2023, as compared to 2010 to 2015, reflects substantial changes in the technological and academic environments. The evolution of digital technology has enhanced educational practices, with greater incorporation of technology into teaching and administration. The COVID-19 pandemic has also accelerated the adoption of digital tools in education, underscoring the necessity to keep pace with ongoing technological developments.

Our study highlights the combined effects of digital technology and educational efficiency, emphasizing the importance of sustained investment and strategic planning in human capital development to stay aligned with technological advancements.

7. Robustness check

To strengthen the robustness of our model, we implement several validation measures and test alternative indicators for both the dependent variable and the metrics for educational quality and technology proficiency. We also utilize a range of estimation techniques to verify the reliability of our findings.

Firstly, we analyze economic development through different metrics Hawkes and Ugur (2012) recommended, including per capita GDP growth, total factor productivity (TFP), and gross domestic product growth rate. Our primary focus is on per capita GDP growth, but we also use it as an alternative metric to cross-verify our results (see column 1).

We assess educational quality indicators like the ratio of teachers to students and the qualifications of educators. In particular, we use the proportion of teachers holding valid certifications or licenses as an alternative measure (see column 2). This method is supported by Cabardo et al. (2014) and Dedrick et al. (2003), emphasizing the role of teacher qualifications in evaluating educational standards.

To address the difficulties in obtaining accurate data on technology proficiency, we propose an alternative measure: government expenditure on digital technology. This approach assumes that increased spending in this sector could significantly enhance technology proficiency among both educators and students (see column 3), as supported by Sul (2017), Agustina and Pramana (2019).

The robustness checks in Appendix Table A7 indicate that although educational quality and technology proficiency still positively influence economic development, the coefficients are somewhat lower than those observed in the baseline regression. The combined effect of these two factors remains positive but shows reduced coefficients. These results are consistent across various estimation methods, incorporating the GMM, Maximum Likelihood Estimation (see column 4), and the Anderson-Hsiao estimator (see column 5). Nonetheless, we observe a reduced significance of many coefficients in these alternative models, suggesting that the GMM approach may be more suitable due to its better handling of endogeneity issues.

8. Conclusions

Our research highlights the combined effect of technology proficiency and educational efficiency, demonstrating how technological advancements can significantly improve academic outcomes and drive economic growth. This synergy is particularly evident in low-income countries, where the potential for substantial growth challenges conventional expectations.

Although our findings are insightful, existing literature lacks effective measures for assessing educational efficiency and competencies. We introduce a new approach utilizing indicators from SDG 4 of the United Nations (n.d.) to address this gap. However, the reliance on scores and self-evaluations to construct the educational efficiency index may introduce limitations in accuracy.

Our results suggest that policymakers should concentrate on investments that enhance education and technology. Essential initiatives include modernizing educational infrastructure, improving teacher training, and increasing technological resources. Developing a standardized numerical database to assess educational and competency quality requires collaboration with international organizations and experts to ensure accurate and comparable metrics. Continuous evaluation and updates are necessary to monitor progress and support evidence-based policy decisions, fostering sustainable economic development.

Future research should explore the underlying mechanisms driving the positive effects of technology proficiency and educational efficiency on economic growth. Longitudinal studies could provide deeper insights into how these effects evolve and their long-term sustainability. Additionally, sector-specific analyses may reveal how improvements in technology and education influence various industries differently. A comprehensive understanding of how these advancements contribute to economic development, along with identifying potential mediating factors, will offer a richer perspective on these dynamics.

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APPENDIX

Table A1. Selected countries

High income	Middle income	Low income
Austria	China	Ethiopia
Australia	Brazil	Central African Republic
Belgium	Argentina	Mozambique
Canada	Mexico	Chad
Denmark	Colombia	Rwanda
Finland	Peru	Sierra Leone
France	Bolivia	South Sudan
Germany	Paraguay	Somalia
Greece	Malaysia	Guinea-Bissau
Hungary	Indonesia	Yemen, Rep.
Italy	Thailand	Burkina Faso
Luxembourg	Türkiye	Syria (Syrian Arab Republic)
Netherlands	South Africa	Uganda
Saudi Arabia	Namibia	Afghanistan
Spain	Cameroon	Burundi
Sweden	Pakistan	Gambia
Switzerland	Belarus	Congo, Dem. Rep
United Kingdom	Serbia	Eritrea
	Montenegro	Togo
	Costa Rica	Korea, Dem. People's Rep.
	El Salvador	Haiti
	Belize	Mali
	Maldives	Madagascar

Note: The categorization of countries by income levels follows the classification set by the World Bank (n.d.).

Table A2. Description of variables (source: authors' presentation)

Variable	Notation	Definition	dataset
economic development	GDP_growth	GDP growth rate	World Development Indicators (WDI) (World Bank, n.d.)
Key variables			
technology proficiency	ICT	the percentage of young people and adults who possess ICT competencies	Global SDG Database (United Nations, n.d.)
Educational efficiency	EDU	A composite index measures four components: Curricula (CURR), National Education Policies (NEP), Student Assessment (SA), and Teacher Education (TE), with scores ranging from 0 to 4.	Self-building index

End of Table A2

Variable	Notation	Definition	dataset
Educational efficiency measures			
national education policies	NEP	index that evaluates how well a country's education policies incorporate and support sustainable development.	National Ministers of Education
curricula	CURR	measures the extent to which educational curricula incorporate elements of sustainable development goals.	National Ministers of Education
Teacher education	TE	measures the number of educators who have received specialized training or education	National Ministers of Education
Student assessment	SA	evaluates the methods and processes used to evaluate students' understanding and competencies	National Ministers of Education
Factors influencing GDP growth			
government consumption	CONS	proportion of government consumption relative to GDP	WDI (World Bank, n.d.)
institutionnal quality	IQ	index measuring the quality of institutions	WDI (World Bank, n.d.)
physical infrastructure	PI	Infrastructure Investment Index	World Economic Forum (n.d.)
inflation rate	INF	Fluctuations in consumer price indices	WDI (World Bank, n.d.)
fertility rate	FERT	average number of children a woman is expected to have over her lifetime, based on current birth rates	WDI (World Bank, n.d.)
global investment	INV	gross investment-to-GDP ratio	WDI (World Bank, n.d.)
foreign direct investment	FDI	Total of foreign direct investment	WDI (World Bank, n.d.)

Table A3. Descriptive statistics (source: authors' calculations)

Variable	Mean	Std. Dev.	Min	Max
CONS	4.5202	0.2264	–1.33	23.51
EDU	2.1490	0.0135	0	4
ICT	0.3384	0.8090	0	1
NEP	0.4804	0.2711	0	1
CURR	0.3492	0.1833	0	1
TE	0.2962	0.3330	0	1
SA	0.4211	0.1653	0	1
GDP_growth	1.5362	0.1180	–6.58	7.24
IQ	0.5521	0.2348	0	1
PI	6.1015	2.3270	3.2658	21.6542
INF	5.4135	1.3768	1.135	42.7152
FERT	6.1863	5.5226	2.8261	29.3654
INV	5.3812	2.1358	1.6233	56.4254
FDI	35.64	12.05	4.35	121.25
ICTxEDU	3.0562	0.0846	0	3.6945

Table A4. Tests for stationarity (source: authors' calculations)

Variable	ADF		PP	
	Levels	First differences	Levels	First differences
GDP_growth	1.0042*	2.4812**	1.0579	3.1544**
ICT	0.7276	1.8524*	0.8785	2.0328**
EDU	1.2278	3.6581*	1.6947	4.6227*
NEP	1.2671	2.6582*	1.9675	3.0385**
CURR	3.1495	3.6821*	2.367	3.1191*
TE	5.0685	6.6284**	6.1102	7.5694*
SA	3.1277	4.2007*	2.6857	2.1121*
CONS	5.1377	3.6247*	5.2771	3.1107*
IQ	1.0015	4.1157**	1.5522	3.5264*
PI	8.0267	11.0248**	7.9529	13.1153**
INF	5.0382	14.0117*	6.1187	15.0574*
FERT	3.1137	4.6558*	2.0757	8.6284*
INV	5.3858	2.3954*	5.1984	2.0583**
FDI	11.8532	13.1174*	11.0574	16.8534*
ICTxEDU	1.0945	3.0510*	3.0068	3.8627*

Table A5. Educational efficiency, technology proficiency, and economic development, baseline model

	(1)	(2)	(3)	(4)	(5)
GDP_growth_{t-1}	0.041*** (0.001)	0.031** (0.015)	0.041** (0.020)	0.022*** (0.011)	0.042*** (0.015)
ICT	0.016** (0.008)	0.017* (0.008)	0.008* (0.004)	0.011* (0.005)	0.076** (0.038)
CONS	0.010* (0.005)	0.063** (0.031)	0.021* (0.010)	0.044** (0.022)	0.052** (0.026)
IQ	0.416* (0.212)	0.211*** (0.101)	0.401** (0.200)	0.587** (0.293)	0.321** (0.160)
PI	0.052* (0.026)	0.014* (0.007)	0.032* (0.017)	0.337 (0.511)	–0.141 (0.073)
INF	–0.024* (0.012)	0.009** (0.004)	–0.032 (0.411)	–0.051 (0.110)	0.027** (0.013)
FERT	0.042** (0.021)	0.018* (0.009)	0.014 (0.207)	0.021* (0.010)	0.017 (0.098)
INV	0.193* (0.098)	0.128* (0.065)	0.148** (0.074)	0.087** (0.043)	0.074** (0.037)
FDI	0.054* (0.027)	0.025 (0.307)	0.103 (0.577)	0.094* (0.047)	0.031* (0.015)
EDU		0.026** (0.013)	0.025** (0.012)	0.018* (0.009)	0.042** (0.021)
ICTxEDU			0.039*** (0.010)	0.038** (0.019)	0.061** (0.030)

End of Table A5

	(1)	(2)	(3)	(4)	(5)
R-squared (within)	0.35	0.29	0.42	0.37	0.31
F-test	2.86***	2.17***	3.24***	3.55***	2.38***
test of Hansen / p-value	(0.086)	(0.109)	(0.213)	(0.091)	(0.081)
AR(1) / p-value	(0.001)	(0.002)	(0.000)	(0.002)	(0.001)
AR(2) / p-value	(0.237)	(0.072)	(0.108)	(0.169)	(0.453)
# of countries	64	64	64	64	64
# of observations	726	738	781	755	748

Note: Table 5 estimates equation (2). In column (1), the GMM estimator is used, excluding the educational efficiency variable and the interaction term. Column (2) introduces the educational efficiency variable, while column (3) displays the whole model, incorporating the interaction term. Estimates for 2010–2015 are presented in column (4), and column (5) covers the results for 2016–2021. The significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% significance levels, respectively.

Table A6. Educational efficiency, technology proficiency, and economic development – income category countries

	(1)	(2)	(3)
GDP_growth_{t-1}	0.062*** (0.012)	0.021** (0.010)	0.031** (0.015)
ICT	0.041** (0.020)	0.019* (0.010)	0.042** (0.024)
CONS	0.031* (0.015)	0.048** (0.024)	0.052** (0.026)
IQ	0.051 (0.360)	0.097* (0.049)	0.081** (0.040)
PI	0.030* (0.015)	–0.237 (0.511)	–0.141 (0.373)
INF	–0.022* (0.011)	–0.051 (0.098)	–0.027* (0.013)
FERT	0.021* (0.011)	0.015* (0.007)	0.057 (0.398)
INV	0.068** (0.034)	0.087* (0.043)	0.032** (0.016)
FDI	0.087 (0.127)	0.094 (0.347)	0.041* (0.021)
EDU	0.045** (0.022)	0.018* (0.009)	0.012** (0.006)
ICTxEDU	0.061** (0.030)	0.032* (0.016)	0.016** (0.008)
R-squared (within)	0.31	0.23	0.24
F-test	1.38***	2.55**	3.08**
# of countries	23	23	18
# of observations	275	264	174

Note: Table 6 estimates equation (2), with GDP growth as the dependent variable. Column (1) shows the results for low-income countries, while column (2) focuses on middle-income countries and column (3) reports findings for high-income countries. Significance is marked by ***, **, and *, indicating significance levels of 1%, 5%, and 10%, respectively.

Table A7. Robustness checks

	(1)	(2)	(3)	(4)	(5)
GDP_growth_{t-1}	0.031** (0.015)	0.022** (0.011)	0.018* (0.009)	0.019** (0.009)	0.025** (0.012)
ICT	0.010** (0.005)	0.015* (0.007)	0.023* (0.011)	0.012* (0.006)	0.016* (0.008)
CONS	0.011** (0.005)	0.013** (0.006)	0.017 (0.019)	0.013* (0.006)	0.009* (0.004)
IQ	0.026* (0.013)	0.031** (0.015)	0.021** (0.010)	0.017 (0.093)	0.011* (0.005)
PI	0.022* (0.011)	0.011* (0.005)	0.032 (0.087)	0.337 (0.511)	–0.141 (0.973)
INF	–0.031* (0.016)	0.010** (0.005)	–0.062 (0.411)	–0.051 (0.310)	0.027* (0.013)
FERT	0.035** (0.017)	0.012* (0.006)	0.014 (0.367)	0.021* (0.080)	0.017 (0.598)
INV	0.073* (0.036)	0.058* (0.029)	0.038* (0.019)	0.027* (0.013)	0.024* (0.012)
FDI	0.024* (0.012)	0.035 (0.307)	0.123 (0.577)	0.094* (0.047)	0.011* (0.005)
EDU	0.021** (0.010)	0.018** (0.009)	0.025** (0.012)	0.021* (0.010)	0.022** (0.011)
ICTxEDU	0.028* (0.014)	0.035** (0.017)	0.019** (0.009)	0.018* (0.009)	–0.011 (0.755)
R-squared (within)	0.20	0.23	0.19	0.29	0.30
F-test	1.86**	3.01**	2.84***	3.05**	3.38**
# of countries	64	64	64	64	64
# of observations	722	739	746	772	782

Note: Column (1) uses per-capita GDP growth as an alternative dependent variable. In column (2), the analysis shifts to a different indicator of education quality, emphasizing teacher qualifications. Column (3) introduces an alternative measure for technology proficiency, using information and communication technology expenditure as a percentage of GDP. Columns (4) and (5) apply different estimation techniques: Maximum Likelihood Estimation in column (4) and the Anderson-Hsiao estimator in column (5).