The Impact Of Mean Years Of Schooling And Patent Applications On GDP Per Capita With Labor Productivity As A Mediating Variable In Asean-4

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Abstract: *This study examines the effect of mean years of schooling and patent applications on GDP per capita in ASEAN countries, both directly and indirectly through labor productivity as a mediating variable. All variables were transformed into natural logarithms (ln), and the analysis employed path analysis based on panel data regression, consisting of two structural equations. Structural Model 1 estimates the effect of the independent variables on the mediating variable, while Structural Model 2 estimates the effect of both the independent variables and the mediating variable on the dependent variable. Based on model selection tests, the Random Effect Model (REM) was selected for Structural Model 1, and the Fixed Effect Model (FEM) was selected for Structural Model 2. The results show that mean years of schooling (RRLS) has a positive and significant effect on GDP per capita, both directly and indirectly through labor productivity. This indicates that education contributes to economic output mainly through its role in enhancing labor productivity. Patent applications also show a positive and significant effect on GDP per capita, both directly and indirectly. Although smaller in magnitude than education, this confirms that innovation activity supports economic growth in ASEAN primarily through labor productivity gains. Overall, labor productivity serves as a key mediating channel linking human capital and innovation to GDP per capita across ASEAN countries, with indirect effects outweighing direct effects for both variables.*

INTRODUCTION

A nation's success in achieving genuine economic transformation is commonly assessed through its progress in economic development. Sen (1999) frames this process not merely as numerical growth but as the expansion of people's capabilities and freedoms, reflected in rising per capita income, improved access to education, and narrowing social inequality. To map development positions across countries, the World Bank classifies nations into four income groups based on Gross National Income (GNI) per capita. However, a considerable number of countries remain stalled at the middle-income level and fail to advance toward high-income status a condition widely known as the *middle-income trap*. The World Bank (2024) reports that of roughly 142 countries that have passed through the middle-income stage, only 34 successfully transitioned to high-income status within two to three decades, while the remaining 108 countries have stayed at this level for extended periods, together accounting for nearly 40 percent of global economic output.

This study focuses on four ASEAN countries Indonesia, the Philippines, Thailand, and Malaysia as they meet the criteria set by the World Bank Institute for Economic Development (2023) for countries that have remained in the middle-income category for two to three decades. Indonesia, for instance, only reached lower-middle-income status in 2005, while the Philippines has remained at that level since 1995. Thailand and Malaysia, despite advancing to upper-middle-income status, have yet to cross the threshold into high-income status. Notably, although the nominal GDP per capita of these four countries has continued to rise over the long term, their growth rates have weakened and become increasingly volatile since the 1998 monetary crisis. This pattern suggests that recent gains have largely been sustained by residual momentum from earlier growth periods rather than by new, robust drivers reinforcing the indication that these countries are experiencing a middle-income trap.

In response to this challenge, the World Bank (2024) has called for a policy shift away from physical capital accumulation toward strategies grounded in innovation and human capital development. Mean years of schooling is frequently used as a proxy for human capital, as it is assumed to reflect the stock of knowledge and skills embedded in the workforce (Glaeser et al., 2004). Historical data show that all four ASEAN countries have recorded steady increases in mean years of schooling since 1990, with Malaysia achieving the most notable progress by surpassing ten years of schooling since the mid-2010s, while Indonesia posted the sharpest improvement despite starting from the lowest baseline. Nevertheless, an average of eight to ten years of schooling still falls well short of the standard observed in advanced economies, which typically exceeds twelve years raising questions about whether current educational attainment in the region is sufficient to stimulate meaningful innovation and productivity gains.

The relationship between human capital accumulation and economic growth remains contested in the literature. On one hand, Mankiw et al. (1992) argue, consistent with endogenous growth theory, that investment in education directly contributes to national prosperity. On the other hand, Pritchett (2001) finds that increases in years of schooling in developing countries are not always accompanied by corresponding gains in output per worker, a phenomenon he attributes to *credentialism* education pursued merely to obtain formal qualifications without a genuine improvement in practical skills. Hanushek and Woessmann (2012) further argue that what truly drives economic outcomes is not the duration of schooling but the cognitive skills actually acquired during that time.

Beyond education, a country's innovative capacity commonly measured through patent applications is also regarded as a crucial link between human capital and accelerated GDP per capita growth, as proposed by Romer (1990) within the endogenous growth framework. Patent application trends across ASEAN-4 vary considerably: Thailand and Malaysia have maintained relatively higher and more consistent levels compared to Indonesia and the Philippines, while

Indonesia experienced a notable surge, exceeding 3,000 applications in 2019 before subsequently declining. Even so, when compared to innovation leaders such as Japan and South Korea which routinely record hundreds of thousands of patent applications annually the ASEAN-4 countries remain far behind. The literature on this issue is similarly divided: Inayah and Sugiyanto (2023) as well as Chen and Puttitanun (2005) find that patent protection positively affects economic growth, whereas Gould and Gruben (1996) and Boldrin and Levine (2007) caution that patents may generate market inefficiencies or be misused as barriers to competition, particularly under overly protective trade regimes.

The apparent gap between ongoing investments in education and innovation, on one hand, and the persistently sluggish growth of GDP per capita, on the other, suggests that a critical transmission link in the economic mechanism may not be functioning optimally. It is at this juncture that labor productivity emerges as a strategic mediating factor, converting accumulated knowledge and technological capacity into tangible economic output. Eichengreen et al. (2013) contend that the root cause of the middle-income trap often lies in the stagnation of labor productivity before a country manages to catch up with advanced economies. In other words, regardless of how substantial investments in education and patents may be, their impact on GDP per capita will remain limited unless they succeed in enhancing labor productivity; conversely, when such investments effectively accelerate labor productivity, productivity itself becomes the primary driver of GDP per capita growth.

This distinction between direct and indirect mechanisms of influence is analytically important to avoid misinterpretation. Theoretically, mean years of schooling and patent applications may directly affect GDP per capita by expanding the national knowledge stock and enhancing market efficiency. At the same time, both variables may also operate indirectly by strengthening individual work capacity. Overlooking either pathway risks producing a biased understanding of how cognitive and technological factors are transmitted into national development outcomes.

The situation observed in ASEAN-4 reflects an underlying paradox: governments have made considerable efforts to extend educational attainment and stimulate innovation through patent systems, yet GDP per capita growth remains slow and continues to be overshadowed by the risk of the middle-income trap. This gap between policy effort and outcome underscores the need for empirical evidence to determine whether human capital (mean years of schooling) and innovation (patent applications) predominantly influence GDP per capita directly, or whether their effectiveness is largely contingent on their capacity to enhance labor productivity as an indirect pathway. Building on this background, the present study aims to examine and analyze the direct effect of mean years of schooling and patent applications on GDP per capita, as well as their indirect effect through labor productivity as a mediating variable, across four ASEAN countries Indonesia, the Philippines, Thailand, and Malaysia over the period 1990–2023.

THEORITICAL

In contrast to the Solow growth model, which treats technological progress as an exogenous element originating outside the economic system, endogenous growth theory developed by Romer (1986) and Lucas (1988) regards technological advancement as an outcome generated from within the economy itself. Under this framework, a country's rate of economic growth is largely determined by its capacity to accumulate knowledge through human capital, sustain innovative activity, and independently build technological capabilities.

This theoretical framework can be expressed through the production function Y = f(K, H, R), where Y represents economic output or GDP per capita, K denotes the accumulation of physical capital, H reflects human capital, and R captures research, development, and innovation activities. What distinguishes this theory from classical growth models is the non-rival nature of H and R, which generate positive spillover effects across the broader economy. This characteristic gives rise to increasing returns to scale, whereby sustained investment in education and research can offset the diminishing returns typically associated with conventional factors of production, thereby enabling per capita income to grow continuously over the long run.

Lucas (1988), together with Romer (1986, 1990), positions human capital as a central driver of long-term economic growth. Rather than functioning merely as a complementary input, human capital in this framework serves a dual role: it acts as a factor of production while simultaneously serving as the primary source of new knowledge and innovative ideas. The underlying logic is straightforward a more educated and skilled workforce tends to be more productive and better equipped to generate ideas that enhance the efficiency of the production process.

This study adopts mean years of schooling as a proxy for human capital, based on the premise that longer educational duration reflects a greater accumulation of knowledge and skills within an economy. The underlying causal pathway suggests that an increase in mean years of schooling enhances the workforce's knowledge base, which in turn raises labor productivity, and ultimately contributes to higher GDP per capita. Following this logic, human capital is expected to influence GDP per capita through two distinct channels directly, and indirectly through the enhancement of labor productivity.

This perspective aligns with Becker (1964, as cited in Surbakti et al., 2024), who argues that education equips workers with competencies that make them more productive and capable of earning higher incomes. Huy et al. (2024) further note that education does not operate in isolation but complements health as a component of human capital formation, with both elements serving as essential foundations for sustainable development and long-term economic competitiveness.

Consistent with Romer's (1986) original proposition, research, development, and innovation are not regarded as factors arriving from outside the economic system but rather as outcomes generated through the economic process itself. Empirical evidence from Hasan and Tucci (2010) reinforces this argument, demonstrating that innovation and technological progress play a critical role in a country's economy not only by improving efficiency but also by opening new market opportunities that expand the existing technological frontier. Audretsch (1995, as cited in Hasan & Tucci, 2010) further observes that innovation fosters conditions that encourage entrepreneurs to enter new industries, thereby accelerating overall economic dynamism. In other words, innovation generates not only new technologies but also gives rise to new firms.

Yang (2006) notes that the number of patent applications is commonly used in empirical research as an indicator of a country's level of innovation and technological advancement. Within the production function $Y = f(K, H, R)$, patents represent a concrete manifestation of the R component the tangible output of research and development activities that contribute to production efficiency and enhance the productivity of factors of production. A higher volume of patent applications reflects a country's greater capacity to continue advancing the quality of its innovation and strengthening its technological capabilities over time.

METHOD

The research model in this study is designed to examine the effect of mean years of schooling and patent applications on GDP per capita, both directly and indirectly through labor productivity as a mediating variable. To capture these relationships, the study employs two structural equations estimated using a panel data regression approach with EViews and Stata software. The first equation estimates the effect of mean years of schooling and patent applications on labor productivity as the mediating variable. The second equation then estimates the direct effect of mean years of schooling, patent applications, and labor productivity on GDP per capita as the dependent variable. The regression coefficients obtained from both equations subsequently serve as the basis for path analysis, which is used to calculate the direct effect, the indirect effect through labor productivity as the mediating variable, and the total effect among the variables under study.

$\text{lnPTK}_{it} = \alpha_1 + \beta_{11}\text{lnRRLS}_{it} + \beta_{12}\text{lnPATEN}_{it} + e_{1it}$ (Struktural 1)
$\text{lnGDPCAP}_{it} = \alpha_2 + \beta_{21}\text{lnRRLS}_{it} + \beta_{22}\text{lnPATEN}_{it} + \beta_{23}\text{lnPTK}_{it} + e_{2it}$ (Struktural 2)

Where:

lnGDP : Natural logarithm of GDP per capita
β : Regression coefficient of each variable
lnRRLS : Natural logarithm of mean years of schooling
lnPaten : Natural logarithm of the number of patent applications
lnPTK : Natural logarithm of labor productivity
ε : Error term
i : Cross-section (Indonesia, the Philippines, Thailand, and Malaysia)
t : Time series (1990–2023)

RESULT AND DISCUSSION

Some of the approaches in the data panel are the common effect model, fixed effect model, and random effect model. The tests to find the most appropriate model are the chow test, the thirst test and the LM (langrange multiplier) test.

Table 1. Chow test result

Struktural 1		Struktural 2	
Statistik Uji	Nilai	Statistik Uji	Nilai
F-statistic	498,55	F-statistic	143,92
Df	(3;130)	Df	(3;129)
Prob>F	0,0000	Prob>F	0,0000

Source: Processed data (2026)

Table 1 shows that the results of the Chow Test for both Structural Model 1 and Structural Model 2 indicate that the Fixed Effect Model (FEM) is the selected model, with a probability value of < 0.05.

Table 2. Hausman test result

Struktural 1		Struktural 2	
Statistik Uji	Nilai	Statistik Uji	Nilai
F-statistic	4,98	F-statistic	101,63
Df	2	Df	3
Prob> Chi-Square	0,0830	Prob> Chi-Square	0,0000

Source: Processed data (2026)

Based on the Hausman Test results presented in Table 2, the Random Effect Model (REM) was selected for Structural Model 1, with a probability value (Prob > Chi-square) of 0.0830, which exceeds the 0.05 significance level. For Structural Model 2, the Fixed Effect Model (FEM) was selected, with a probability value (Prob > Chi-square) of 0.0000, which is below the 0.05 significance level. Consequently, Structural Model 1 proceeded to the Lagrange Multiplier (LM) Test, while the final model selected for Structural Model 2 is the Fixed Effect Model.

Table 3. LM test result

Statistik Uji	Nilai
$chibar^2(01)$	1585,45
Prob > $chibar^2$	0,0000

Source: Processed data (2026)

Based on the Lagrange Multiplier (LM) Test results presented in Table 3, the final model selected is the Random Effect Model (REM), as the probability value (Prob > Chibar) of 0.0000 is below the 0.05 significance level. Therefore, it can be concluded that, based on the panel data model selection procedure, the Random Effect Model (REM) was selected for Structural Model 1, while the Fixed Effect Model (FEM) was selected for Structural Model 2.

Table 4. Regression result struktural 1

Variable (M) : ln Produktivitas Tenaga Kerja				
Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
C	8,490294	0,261726	32,43967	0,0000
lnRRLS	0,554283	0,136011	4,075280	0,0003
lnPaten	0,090035	0,024353	3,697103	0,0008
R-squared	0,735982			
Adjusted R-Squared	0,732012			
F-Statistic	185,3766			
Prob(F-statistic)	0,000000			

Source: Processed data (2026)

$$PTK_{it} = 8{,}490294 + 0{,}554283\, RRLS_{it} + 0{,}090035\, Paten_{it} + \nu_{it}$$

Table 5. Regression result struktural 2

Variable (Y) : ln GDP per kapita				
Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
C	-1,80702	0,36492	-4,95	0,000
lnRRLS	0,10598	0,04138	2,56	0,015
lnPaten	0,02635	0,09852	2,67	0,012
lnPTK	1,06108	0,04487	23,65	0,000
Within R-squared	0,9713			
F-Statistic	4224,94			
Prob(F-statistic)	0,00000			

Source: Processed data (2026)

$$GDPcap_{it} = -1{,}80702 + 0{,}10598\, RRLS_{it} + 0{,}02635\, Paten_{it} + \beta 3\ 1{,}06108\, PTK_{it} + \varepsilon_{it}$$

Table 6. t-test result

Struktural 1				
Variabel	**t-statistik**	**t-tabel**	**Probabilitas**	**Kesimpulan**
lnRRLS	4,0752	1,66	0,0003	H_0 ditolak
lnPaten	3,6871	1,66	0,0008	H_0 ditolak
Struktural 2				
Variabel	**t-statistik**	**t-tabel**	**Probabilitas**	**Kesimpulan**
lnRRLS	2,56	1,66	0,015	H_0 ditolak
lnPaten	2,67	1,66	0,012	H_0 ditolak
lnPTK	23,65	1,66	0,000	H_0 ditolak

Source: Processed data (2026)

The results of the t-test indicate that, in both Structural Model 1 and Structural Model 2, all variables show a probability value of < 0.05, indicating a positive and significant effect. Specifically, mean years of schooling (RRLS) and patent applications have a positive and significant effect on the mediating variable, labor productivity (PTK). Furthermore, mean years of schooling, patent applications, and labor productivity all have a positive and significant effect on GDP per capita.

Table 7. Path Analysis result

Jalur Variabel	Pengaruh Langsung (*Direct Effect*)	Pengaruh Tidak Langsung (*Indirect Effect*)	Pengaruh Total (*Total Effect*)
lnRRLS→lnGDPcap	b_{21} 0,105986	b_{11} x b_{23} 0,554283 x 1,06108 = 0,588144	b_{21} + (b_{11} x b_{23}) 0,694130
lnPaten→lnGDPcap	b_{22} 0,026352	b_{12} x b_{23} 0.090035 x 1.06108 = 0,095535	b_{22} + (b_{12} x b_{23}) 0,121887
lnPTK→lnGDPcap	b_{23} 1,061089	-	b_{23} 1,061089

Source: Processed data (2026)

Sobel test

$$Z_{\text{RRLS}} = \frac{\beta_{11} \cdot \beta_{23}}{\sqrt{\beta_{23}^2 \cdot \left(SE_{\beta_{11}}\right)^2 + \beta_{11}^2 \cdot \left(SE_{\beta_{23}}\right)^2}}$$

$$Z_{\text{RRLS}} = \frac{0{,}554283 \cdot 1{,}061089}{\sqrt{(1{,}061089)^2 \cdot (0{,}136011)^2 + (0{,}554283)^2 \cdot (0{,}044873)^2}}$$

$$Z_{\text{RRLS}} = \frac{0{,}588144}{0{,}146445} = 4{,}016140$$

$$Z_{\text{PATEN}} = \frac{\beta_{12} \cdot \beta_{23}}{\sqrt{\beta_{23}^2 \cdot \left(SE_{\beta_{12}}\right)^2 + \beta_{12}^2 \cdot \left(SE_{\beta_{23}}\right)^2}}$$

$$Z_{\text{PATEN}} = \frac{0{,}090035 \cdot 1{,}061089}{\sqrt{(1{,}061089)^2 \cdot (0{,}024353)^2 + (0{,}090035)^2 \cdot (0{,}044873)^2}}$$

$$Z_{\text{PATEN}} = \frac{0{,}095535}{0{,}026153} = 3{,}652931$$

The results of the Sobel test show that the calculated Z-values for both pathways Structural Model 1 and Structural Model 2 exceed the critical Z-table value of 1.96. This indicates that labor productivity is confirmed to significantly mediate the relationship between both mean years of schooling and patent applications, and GDP per capita.

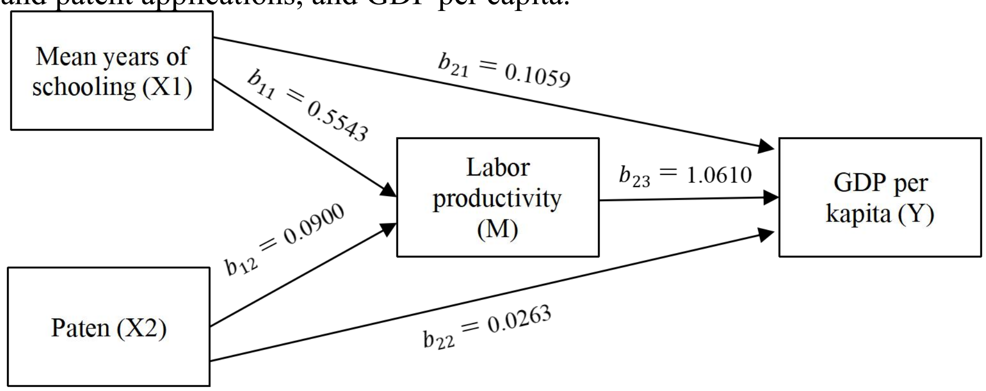

Figure 1. Path Diagram result

The relationship between Mean years of schooling (X1) and GDP per capita (Y) through labor productivity (M)

The results of the path analysis show that mean years of schooling also has an indirect effect on GDP per capita through labor productivity (PTK) as the mediating variable, with an indirect effect value of 0.58814. This value is obtained by multiplying the coefficient of the effect of mean years of schooling on labor productivity (0.5543) by the coefficient of the effect of labor productivity on GDP per capita (1.0610). The magnitude of the indirect effect of mean years of schooling on GDP per capita through labor productivity (0.58814) is considerably greater than its direct effect, which amounts to only 0.1059. This indicates that the impact of education on income per capita operates predominantly through improvements in labor productivity rather than directly. In other words, education does not instantly translate into higher income per capita; rather, it must first be converted into enhanced workforce capacity and efficiency.

The total effect of mean years of schooling on GDP per capita, obtained by summing the direct effect (0.1059) and the indirect effect (0.58814), amounts to 0.694130. This figure indicates that a 1 percent increase in mean years of schooling through both the direct pathway and the pathway mediated by labor productivity increases GDP per capita by 0.694130 percent overall. This total effect also shows that approximately 84.7 percent of the total effect of mean years of schooling on GDP per capita is transmitted through the indirect pathway via labor productivity, while the remaining 15.3 percent represents the direct effect.

The dominance of the indirect effect over the direct effect indicates that labor productivity serves as a dominant mediator in the relationship between mean years of schooling and GDP per capita. This finding reinforces Human Capital Theory as proposed by Schultz (1961) and Becker (1964), which essentially emphasizes that the economic benefits of education do not emerge automatically but must first be channeled through improvements in work productivity as a tangible manifestation of higher-quality human resources. This finding carries important policy implications for Indonesia, the Philippines, Thailand, and Malaysia in their efforts to escape the middle-income trap: investment in education will generate a substantially greater impact on GDP per capita when accompanied by policies that explicitly ensure such educational gains are genuinely converted into real improvements in labor productivity. Policies such as aligning educational curricula with labor market needs (link and match), competency-based vocational training, and apprenticeship programs that connect graduates with the industrial sector are therefore crucial, so that the accumulation of years of schooling does not remain merely an administrative achievement, but is genuinely manifested in higher labor productivity that sustainably increases output per capita.

Patent Applications (X2) on GDP per capita (Y) via labor productivity (M)

The results of the path analysis show that patent applications also have an indirect effect on GDP per capita through labor productivity (PTK) as the mediating variable, with an indirect effect value of 0.09553. This value is obtained by multiplying the coefficient of the effect of patent applications on labor productivity (0.0900) by the coefficient of the effect of labor productivity on GDP per capita (1.0610).The magnitude of the indirect effect of patent applications on GDP per capita through labor productivity (0.09553) is also greater than its direct effect, which amounts to only 0.0263. This pattern is consistent with that observed for mean years of schooling, indicating that labor productivity likewise serves as the primary pathway through which patent activity influences GDP per capita. In other words, innovation outcomes in the form of patents do not automatically translate into higher GDP per capita; rather, they must first be absorbed and applied by the workforce within the production process in order to generate real economic value.
The total effect of patent applications on GDP per capita, obtained by summing the direct effect (0.0263) and the indirect effect (0.09553), amounts to 0.121887. This figure indicates that a 1 percent increase in patent applications through both the direct pathway and the pathway mediated by labor productivity increases GDP per capita by 0.121887 percent overall. Of this total effect, approximately 78.4 percent is transmitted through the indirect pathway via labor productivity, while the remaining 21.6 percent represents the direct effect. The dominance of the indirect effect indicates that labor productivity also functions as a dominant partial mediator in the relationship between patent applications and GDP per capita. This finding reinforces the argument put forward in Griliches' (1979) knowledge production function and Romer's (1990) endogenous growth theory, which posit that new knowledge generated through innovation activities is essentially an intermediate input whose economic value is only realized once it is absorbed and applied by the workforce in the form of improved efficiency and work quality.

CONCLUSION

Mean years of schooling (RRLS) has a positive and significant direct effect on GDP per capita, with a coefficient of 0.1059, while patent applications likewise have a positive and significant direct effect on GDP per capita, with a coefficient of 0.0263. Both values are relatively small, suggesting that the economic benefits of education and innovation are largely not transmitted directly, but rather through an indirect pathway. Labor productivity is confirmed to serve as a mediator in the relationship between both mean years of schooling and patent applications, and GDP per capita. The indirect effect of mean years of schooling on GDP per capita through labor productivity (0.58814) accounts for approximately 84.7 percent of its total effect (0.694130), while the indirect effect of patent applications through labor productivity (0.09553) accounts for approximately 78.4 percent of its total effect (0.121887). These findings confirm that the economic benefits of education and innovation are only optimally realized once they are first converted into higher labor productivity.

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