International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(7s) 2026 pp. 597-606
https://doi.org/10.70917/ijcisim-2026-3117
Article

# Higher Education and Government Artificial Intelligence Readiness: A Cross-National Analysis

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**Abstract:** Governments' institutional capacity to harness artificial intelligence (AI) varies markedly across countries, and much of the existing literature attributes this disparity to digital infrastructure and income level. This study examines whether the accumulation of human capital through higher education explains additional variance in government AI readiness beyond these structural factors. Drawing on a cross-sectional panel of 158 countries that combines World Bank indicators, governance estimates, and a composite government AI readiness index, robust regression models (HC3), a non-parametric test of between-income-group differences, and a residual correlation analysis were estimated. Gross tertiary enrollment significantly predicted institutional AI readiness ($\beta = 0.19$, $p = .001$), even after controlling for GDP per capita, internet penetration, and government effectiveness. The marginal return of higher education on readiness was significantly smaller in low-income countries than in high-income countries, suggesting an absorptive-capacity threshold rather than a uniform linear effect. Countries whose educational performance exceeded what their income level would predict also showed, on average, higher-than-expected AI readiness performance ($r = .32$, $p < .001$). These findings qualify infrastructure-centered digital divide frameworks, engage with the literature on absorptive capacity and technological catch-up, and position higher education as a relevant, though not sufficient, institutional mechanism for explaining global inequality in AI governance.
**Keywords:** artificial intelligence readiness; higher education; human capital; digital divide; digital governance; absorptive capacity; cross-national analysis

## 1. Introduction

The integration of artificial intelligence (AI) into public administration has become one of the central pillars of the state modernization agenda over the past decade. Initiatives such as Oxford Insights' Government AI Readiness Index have systematically documented that institutional capacity to adopt AI is not evenly distributed across countries; rather, it reproduces, and in certain cases amplifies, pre-existing global economic hierarchies (Oxford Insights, 2025). This phenomenon has predominantly been interpreted through the lens of the digital divide, a concept whose most recent formulation distinguishes at least three levels of inequality: material access to infrastructure, the skills required to use it, and, finally, the outcomes and benefits actually derived from its use (Van Deursen & Helsper, 2015; Ragnedda, 2017).

The literature on institutional AI readiness has nonetheless prioritized the first of these levels: data infrastructure, connectivity, and computational capacity (Oxford Insights, 2025; UNESCO, 2025). Organizations such as Salesforce (2025) have begun to incorporate human capital and skills as an autonomous dimension of national AI readiness, situating it alongside regulatory frameworks, innovation ecosystems, and investment environments. This human capital dimension, however, is rarely operationalized directly through verifiable country-level educational indicators, and is more often approximated through perception surveys or composite indices that are difficult to replicate.

Compounding this empirical gap is a growing normative concern: available evidence suggests that AI may not spontaneously narrow inequality among nations, but instead widen it if lower-income countries fail to simultaneously develop infrastructure, institutions, and human capital (Alonso et al., 2022). This "great divergence" hypothesis has found resonance in recent work documenting how low-income countries remain systematically behind, not only in AI adoption, but also in academic output and policy formulation on the subject (Khan et al., 2024).

At the same time, a well-established tradition in the economics of education positions human capital formation, and higher education in particular, as a determinant of a country's capacity to absorb, adapt, and deploy general-purpose technologies (Becker, 1964; Schultz, 1961). The task-based model developed by Acemoglu and Autor (2011), later extended to automation and artificial intelligence (Acemoglu & Restrepo, 2018), reinforces this connection: an economy's capacity to reallocate its workforce toward tasks that complement technology, rather than being displaced by it, depends critically on the educational attainment of its population. Translated to the institutional plane, this argument suggests that governments with a larger share of tertiary-educated population possess a broader base of technical personnel capable of designing, evaluating, and sustaining AI adoption policies. This logic is further consistent with recent research on transnational digital-influence models, which underscores the need to empirically verify whether institutional mechanisms observed in one country are directly comparable to those of another before generalizing findings across contexts (García-Umaña et al., 2026).

An empirical gap nonetheless persists: no study has established, using globally comparable data, whether higher education enrollment predicts institutional AI readiness once structural factors, namely economic development, digital infrastructure, and governance quality, that the literature already recognizes as determinants are held constant. Nor has it been systematically examined whether this relationship is uniform across income groups, or whether, instead, it operates differently depending on a country's level of development, as the literature on absorptive capacity (Cohen & Levinthal, 1990) and technological catch-up would anticipate. This study occupies that niche: drawing on a cross-sectional panel of 158 countries, it examines the relationship between tertiary enrollment and government AI readiness, assessing its robustness against structural controls, its heterogeneity across income groups, and its expression in terms of relative over- and underperformance.

The study pursues three specific objectives: (a) to determine whether tertiary enrollment predicts institutional AI readiness while controlling for economic development, digital infrastructure, and government effectiveness; (b) to assess whether the marginal return of higher education on such readiness varies by income group; and (c) to examine whether a country's relative educational performance, once adjusted for its income level, is associated with its relative performance in AI readiness. The study further offers a specific reading for the Latin American context, given that the region constitutes one of the subgroups analyzed in greater detail in the discussion.

## 2. Theoretical Framework

### *2.1. Human Capital and Institutional Technological Capacity*

Human capital theory holds that investment in education raises productivity not only at the individual level but also the aggregate capacity of an economy to generate, adopt, and diffuse technological innovation (Schultz, 1961; Becker, 1964). Schultz (1961) argued early on that a substantial share of economic growth left unexplained by physical capital accumulation was, in fact, attributable to investment in the quality of the labor force: education, health, and training. Becker (1964) formalized this intuition, showing that education functions as an investment with measurable economic returns, both private and social. Extended to the institutional plane, this perspective suggests that countries with a larger share of tertiary-educated population possess a broader reserve of technical and administrative personnel capable of designing, evaluating, and sustaining AI adoption policies, regardless of their level of digital infrastructure.

### *2.2. The Task Model and the Technological Bias of Human Capital*

The task-based model of Acemoglu and Autor (2011) offers a more precise causal mechanism for understanding why higher-order human capital may be decisive in the AI era. Under this framework, technology does not uniformly substitute for or complement workers; rather, it reallocates specific tasks between capital and labor according to their relative complexity. Acemoglu and Restrepo (2018) extended this reasoning to the analysis of contemporary automation, showing that the net effect of a new general-purpose technology on employment and productivity depends on whether the economy is able to simultaneously generate new complex tasks, which demand advanced human capital, while automating existing routine tasks. Applied to the level of government, this framework suggests that institutional AI readiness depends not only on possessing technological infrastructure, but on having a critical mass of professionals capable of occupying the new tasks of design, oversight, and evaluation of AI policy that this technology demands; tasks that, by their non-routine nature, fall predominantly to graduates of tertiary education.

### *2.3. The Three Levels of the Digital Divide Applied to AI Governance*

The three-level digital divide framework, namely access, skills, and outcomes, has predominantly been applied to individual technology adoption (Van Deursen & Helsper, 2015; Ragnedda, 2017), including its recent extension to digital public services, where education has been identified as one of the factors most consistently associated with narrowing the gap in the use of such services (Morte-Nadal & Esteban-Navarro, 2025). The present study transposes this framework to the macro-institutional level: just as individual education predicts the transition from mere access to the meaningful use of technology, a country's aggregate higher education attainment may predict the transition from the mere availability of AI infrastructure toward its effective institutional deployment, as measured through government readiness indices. This multilevel analogy, extending from the individual to the institution, constitutes the study's principal theoretical contribution to the digital divide literature.

### *2.4. Absorptive Capacity, Technological Catch-Up, and Development Thresholds*

The literature on absorptive capacity offers a complementary framework, particularly useful for anticipating why the return of human capital on institutional technological capacity might not be linear across levels of development. Cohen and Levinthal (1990) defined absorptive capacity as the ability of an organization, or by extension a country, to recognize the value of new external knowledge, assimilate it, and apply it toward productive ends. This capacity is not automatic: it requires a minimum base of prior knowledge, infrastructure, and institutional stability on which new learning can be anchored. Recent work applied specifically to AI in low-income countries has drawn on this framework to argue that so-called AI catch-up does not follow a single trajectory: some countries with an already consolidated capability base may pursue leapfrogging strategies, while those lacking that base must first strengthen their absorptive capacity before investment in human capital translates into effective institutional capacity (Khan et al., 2024). This theoretical distinction directly anticipates the possibility of a threshold: below a certain level of development, the return of higher education on institutional AI readiness may dissipate, not because education ceases to be valuable, but because other enabling conditions, such as basic connectivity, institutional stability, and sustained public financing, are not yet in place.

### *2.5. The Great Divergence of Artificial Intelligence*

A body of recent economic literature has proposed that, unlike previous technological waves, AI could generate a more pronounced economic divergence between rich and poor countries, insofar as its development and deployment are concentrated in a small number of economies possessing the necessary infrastructure, talent, and capital (Alonso et al., 2022). This "great divergence" hypothesis is consistent with the descriptive findings of this study, in particular a pronounced gradient of institutional AI readiness across income groups, and it motivates the normative question underlying the analysis: which policy levers, among them the expansion of higher education, might mitigate this divergent trajectory?

### *2.6. Expected Heterogeneity by Income Level: A Synthesis of Hypotheses*

Integrating these theoretical bodies, namely human capital theory, the task model, the multilevel digital divide, absorptive capacity, and technological divergence, allows for a more precise formulation of the heterogeneity expectation that guides the study's second specific objective. In low-income contexts, more elementary constraints, such as connectivity, institutional stability, and financing, may act as bottlenecks that limit the marginal return of higher education on AI readiness even where the former exists: absorptive capacity has not yet reached the minimum required threshold. In middle- and high-income economies, by contrast, where basic infrastructure has largely been resolved, higher-order human capital may constitute the differentiating margin that the task model of Acemoglu and Autor (2011) would predict. This threshold hypothesis, rather than a universal linear effect, guides the study's analytical design.

## 3. Method

### *3.1. Design and Data Sources*

A quantitative, non-experimental, cross-sectional design was employed, based on the integration of three public secondary sources at the country level: (a) the World Bank's World Development Indicators (WDI), from which indicators of digital infrastructure, economic development, and education were drawn; (b) government effectiveness estimates from the Worldwide Governance Indicators; and (c) a composite government AI readiness index covering 195 countries (Oxford Insights, 2025). Integrating these sources into a single country-level panel allows the association between educational human capital and institutional AI readiness to be examined with virtually universal geographic coverage, a feature uncommon in the existing literature on this topic, which is concentrated mostly in national or regional case studies (Bangladesh, China) or in theoretical positions without systematic empirical verification at this scale (Khan et al., 2024).

## *3.2. Variables*

The dependent variable was the composite government AI readiness score (the mean of six pillars: policy capacity, AI infrastructure, governance, public sector adoption, development diffusion, and resilience). The main independent variable was the gross tertiary enrollment rate, defined by the World Bank as total enrollment in tertiary education regardless of age, expressed as a percentage of the population in the theoretically corresponding age group. Control covariates included the natural logarithm of GDP per capita (PPP, constant 2021 international dollars), included to stabilize variance and better approximate a linear relationship, the percentage of internet users, and the government effectiveness estimate. Country income group (World Bank: low, lower-middle, upper-middle, and high income) was used both as a grouping factor and as an interaction term.

## *3.3. Analytic Sample*

Of a universe of 217 economies with an available income classification, 194 had an AI readiness score. After listwise deletion of cases with missing values on any variable in the full model, the final analytic sample consisted of 158 countries (low income $n = 15$; lower-middle income $n = 39$; upper-middle income $n = 45$; high income $n = 59$), a figure reported transparently as a coverage limitation rather than as intentional subsampling. The excluded countries corresponded mostly to microstates and economies with lower-capacity national statistical systems, a not entirely random pattern of missing data that is revisited in the limitations section.

## *3.4. Analytic Plan*

The analysis proceeded in four stages. First, descriptive statistics were generated for all variables by income group and by geographic region. Second, given the expected violation of normality and homoscedasticity assumptions in this type of country-level composite index, the non-parametric Kruskal-Wallis test was applied to contrast differences in AI readiness across income groups, accompanied by the epsilon-squared effect size. Third, two linear regression models with heteroscedasticity-robust standard errors (HC3) were estimated: an additive model with tertiary enrollment and the control covariates, and a model with a tertiary enrollment by income group interaction term (with the high-income category as reference), in order to test the heterogeneity-by-development-level hypothesis. Fourth, residuals from two simple regressions, namely tertiary enrollment on the logarithm of GDP per capita, and AI readiness on the same logarithm, were computed and correlated with one another, with the aim of isolating the component of educational over- or underperformance not explained by income and its association with over- or underperformance in AI readiness. All analyses were conducted in Python (pandas, statsmodels, scipy).

## *3.5. Assumption Checks and Multicollinearity Diagnostics*

Prior to interpreting the regression models, the relevant assumptions were verified. The Shapiro-Wilk test applied to the dependent variable within each income group indicated significant departures from normality in the high-income ($W = 0.885$, $p < .001$) and low-income ($W = 0.771$, $p = .002$) groups, while the middle-income groups showed no significant departures (lower-middle: $W = 0.960$, $p = .174$; upper-middle: $W = 0.958$, $p = .104$). This distributional heterogeneity provided a twofold justification for the methodological decision to use the non-parametric Kruskal-Wallis test for the descriptive between-group contrast and heteroscedasticity-robust standard errors (HC3) in the regression models. Levene's test for homogeneity of variance across income groups yielded a result at the margin of conventional significance ($F = 2.43$, $p = .067$), further reinforcing the relevance of this correction. Finally, variance inflation factors (VIF) were computed to rule out severe multicollinearity in the additive model: all predictors fell below the conventional threshold of 10 (tertiary enrollment = 2.20; log GDP per capita = 5.85; internet users = 3.96; government effectiveness = 2.78), although the value for log GDP per capita indicates moderate collinearity with the other predictors, consistent with the strong bivariate association reported in Table 2 and warranting cautious interpretation of the individual coefficients in the additive model.

## 4. Results

### *4.1. Descriptive Analysis by Income Group and Region*

Table 1 presents descriptive statistics by income group. A monotonic gradient is observed in both institutional AI readiness and tertiary enrollment as income rises: low-income countries average 24.2 points on the readiness index (SD = 9.7) and 10.7% tertiary enrollment (SD = 10.0), whereas high-income countries average 62.2 points (SD = 17.1) and 73.1% enrollment (SD = 25.3). It is worth noting that the dispersion of tertiary enrollment, as measured by the standard deviation, increases with income level, suggesting growing heterogeneity in the expansion of higher education among more developed economies.

***Table 1***

*Descriptive statistics by income group*

| Income group | n | GAIRI 2025 M (SD) | Tertiary enrollment % M (SD) | GDP per capita PPP M (USD) | Internet users % M |
|---|---|---|---|---|---|
| Low income | 15 | 24.2 (9.7) | 10.7 (10.0) | 2,314 | 24.6 |
| Lower-middle income | 39 | 38.8 (14.6) | 24.5 (15.3) | 7,572 | 61.4 |
| Upper-middle income | 45 | 44.0 (17.0) | 53.0 (24.9) | 19,557 | 78.9 |
| High income | 59 | 62.2 (17.1) | 73.1 (25.3) | 55,954 | 91.9 |

Table 2 disaggregates the same indicators by World Bank geographic region. Europe and Central Asia (n = 50) exhibits the highest average readiness (M = 59.9) alongside the highest tertiary enrollment (M = 73.1%), whereas Sub-Saharan Africa (n = 33) shows the lowest values on both dimensions (M = 32.0 and M = 13.0%, respectively). Latin America and the Caribbean (n = 25) occupies an intermediate-to-low position, with an average readiness of 39.4 points and average tertiary enrollment of 52.0%, a figure that, unlike institutional readiness, is not far from that of regions with higher AI readiness. This anticipates one of the central findings of the discussion: the region displays comparatively more developed human capital than its institutional AI readiness would suggest.

***Table 2***

*Descriptive statistics by geographic region*

| Region | n | GAIRI 2025 M | Tertiary enrollment % M |
|---|---|---|---|
| Europe and Central Asia | 50 | 59.9 | 73.1 |
| North America | 2 | 81.9 | 77.8 |
| Middle East and North Africa | 19 | 50.5 | 48.3 |
| East Asia and Pacific | 23 | 47.4 | 52.1 |
| South Asia | 6 | 45.9 | 27.0 |
| Latin America and the Caribbean | 25 | 39.4 | 52.0 |
| Sub-Saharan Africa | 33 | 32.0 | 13.0 |

The Kruskal-Wallis test confirmed statistically significant differences in AI readiness across the four income groups, $H(3) = 61.59$, $p < .001$, with a large effect size ($\varepsilon^2 = .38$), corroborating the observed descriptive pattern and positioning income level as a robust, though not exclusive, correlate of institutional AI readiness.

### *4.2. Bivariate Correlations*

Table 3 presents the Spearman correlation matrix among the main variables. Tertiary enrollment correlated positively and substantially with both AI readiness (rho = .69) and the logarithm of GDP per capita (rho = .76), which anticipates the need to isolate its independent effect through multiple regression before attributing explanatory value to it on its own. This elevated correlation among predictors, subsequently confirmed by the VIF diagnostic (Section 3.5), is consistent with the literature documenting how economic development and educational expansion have historically advanced hand in hand (Schultz, 1961).

***Table 3***

*Spearman correlation matrix (N = 158)*

| Variable | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. GAIRI 2025 | — | | | | |
| 2. Tertiary enrollment | .685 | — | | | |
| 3. ln(GDP per capita PPP) | .706 | .759 | — | | |
| 4. Internet users % | .691 | .705 | .855 | — | |
| 5. Government effectiveness | .727 | .639 | .811 | .743 | — |

Note. All correlations are significant at $p < .001$.

### *4.3. AI Readiness and Tertiary Enrollment: The Additive Model (H1)*

The first robust regression model (HC3) evaluated the effect of tertiary enrollment on AI readiness while controlling for the logarithm of GDP per capita, the percentage of internet users, and government effectiveness. The model explained a substantial proportion of variance ($R^2 = .615$, adjusted $R^2 = .605$). Tertiary enrollment showed a positive and statistically significant effect ($\beta = 0.19$, $SE = 0.056$, $z = 3.36$, $p = .001$, 95% CI [0.079, 0.299]), even after controlling for economic development and digital infrastructure. Government effectiveness was also a significant predictor ($\beta = 1.39$, $p < .001$), whereas the logarithm of GDP per capita and the percentage of internet users lost statistical significance once the other predictors were included ($p = .662$ and $p = .334$, respectively), suggesting that much of their bivariate association with AI readiness operates indirectly, through human capital and institutional quality, rather than as independent determinants once both dimensions are controlled for.

These results support Hypothesis 1: the formation of human capital through higher education contributes to explaining institutional AI readiness independently of national wealth and the mere availability of digital infrastructure, consistent with what the task model of Acemoglu and Autor (2011) would predict when applied to the level of government.

### *4.4. Heterogeneity by Income Group: The Interaction Model (H2)*

The second model incorporated the interaction term between tertiary enrollment and income group (reference category: high income), improving model fit ($R^2 = .659$). The slope of tertiary enrollment in the reference group (high income) was 0.26 ($p < .001$). The interaction was significant only for the contrast with the low-income group ($\beta = -0.38$, $SE = 0.186$, $z = -2.05$, $p = .040$), implying a marginal slope close to zero, and even slightly negative ($0.26 - 0.38 \approx -0.13$), for that group. By contrast, the interactions with the lower-middle-income ($\beta = -0.16$, $p = .344$) and upper-middle-income ($\beta = -0.03$, $p = .828$) groups did not reach statistical significance, indicating that the return of tertiary enrollment on AI readiness does not differ in a statistically detectable way between these groups and the high-income group.

This pattern qualifies Hypothesis 2 as originally formulated: rather than a maximum effect in middle-income countries, the data are more consistent with an absorptive-capacity threshold concentrated at the lower end of the income distribution, as anticipated by the framework of Cohen and Levinthal (1990) and revisited by Khan et al. (2024) for the specific case of AI in low-income countries. In low-income countries, the institutional return of tertiary enrollment on AI readiness dissipates, presumably because more elementary constraints, such as basic connectivity, institutional stability, and public financing, act as bottlenecks that prevent educational expansion from translating into governmental technological capacity. Above that threshold, the return of higher-order human capital remains relatively stable across the middle- and high-income groups.

### *4.5. Relative Educational Overperformance and Its Association with AI Readiness (H3)*

To isolate the component of tertiary enrollment not explained by income level, residuals from two simple regressions on the logarithm of GDP per capita were computed: one for tertiary enrollment and one for AI readiness. These residuals represent, respectively, how much more or less tertiary enrollment and how much more or less AI readiness a country exhibits than its income level alone would predict. The correlation between the two sets of residuals was positive and significant ($r = .316$, $p < .001$, $N = 159$), supporting Hypothesis 3: countries that overinvest in higher education relative to their income also tend to show institutional AI readiness above expectations, and vice versa.

Table 4 illustrates this pattern using the countries at the extremes of the tertiary enrollment residual distribution. Cases such as Chile, Argentina, South Korea, and Ukraine combine higher-than-expected tertiary enrollment given their income with equally higher-than-expected AI readiness, whereas economies specialized in natural resources or tourism with high incomes but low relative enrollment, such as Guyana, Suriname, Qatar, and Brunei Darussalam, show the inverse pattern on both dimensions.

***Table 4***

*Countries at the extremes of the tertiary enrollment residual distribution (adjusted for ln GDP per capita) and their corresponding AI readiness residual*

| Country | Tertiary enrollment residual | GAIRI 2025 residual |
|---|---|---|
| Greece | +99.8 | +7.2 |
| Argentina | +49.4 | +10.4 |
| Chile | +49.3 | +8.1 |
| South Korea | +38.7 | +18.2 |
| Ukraine | +38.9 | +17.8 |
| Qatar | −44.5 | −10.7 |
| Brunei Darussalam | −44.1 | −25.8 |
| Suriname | −49.0 | −32.7 |
| Guyana | −51.8 | −39.8 |

## 5. Discussion

### *5.1. Human Capital as an Independent Institutional Mechanism*

The findings of this study offer three contributions to understanding global inequality in institutional AI readiness. First, higher education enrollment predicts such readiness independently of national income and digital infrastructure, supporting the extension of the three-level digital divide framework, originally formulated for individual technology adoption (Van Deursen & Helsper, 2015) and recently applied to digital public services (Morte-Nadal & Esteban-Navarro, 2025), to the macro-institutional plane. Just as individual education explains the transition from access to the effective use of technology, a country's aggregate human capital appears to explain the transition from the mere availability of AI infrastructure toward its effective institutional deployment. This finding is also consistent with the task model of Acemoglu and Autor (2011): institutional AI readiness requires that a country possess the critical mass of professionals capable of occupying the non-routine tasks of design and governance that this technology introduces.

### *5.2. Absorptive-Capacity Thresholds, Not Maximum Returns at Middle Income*

Second, and less anticipated by the original formulation of Hypothesis 2, the return of higher education on AI readiness does not describe a maximum pattern at middle income; instead, it reveals a capacity threshold concentrated at the low-income end of the distribution. This finding is consistent with the absorptive capacity literature (Cohen & Levinthal, 1990) and its recent application to the specific case of AI in low-income countries (Khan et al., 2024): in lower-development contexts, more elementary structural constraints, such as connectivity, institutional stability, and sustained public financing, condition a country's capacity to translate human capital into governmental technological capacity. Only once this minimum absorptive-capacity threshold has been surpassed does investment in higher education appear to translate consistently into greater institutional readiness, a pattern that also resonates with accounts of AI's potential "great divergence" between rich and poor countries (Alonso et al., 2022).

### *5.3. Relative Performance Matters: Lessons for Latin America*

Third, the residual analysis provides evidence that educational human capital matters in relative terms, beyond its absolute level: countries that invest in higher education above what their income would predict also achieve AI readiness above expectations. This result is particularly relevant for the Latin American context. Regional descriptive statistics show that Latin America and the Caribbean exhibits average tertiary enrollment (52.0%) comparable to regions with higher institutional AI readiness, yet an average readiness score (39.4 points) markedly lower, positioning the region as an apparent case of relative underutilization of its aggregate educational human capital. Notwithstanding this aggregate pattern, individual cases such as Chile and Argentina, which rank among the countries with the greatest relative educational overperformance in the global sample, suggest that expanding higher education can constitute an effective public policy lever for institutional technological readiness even in the absence of a full structural transformation of national income, and that the aggregate regional pattern is not homogeneous across countries. This reading is consistent with a recent line of research on the Andean region documenting how digital influence and technology adoption mechanisms operate differently across neighboring countries with similar economic profiles, reinforcing the need not to treat Latin America as a homogeneous bloc when assessing its institutional AI readiness (García-Roldán et al., 2025).

### *5.4. Implications for Public Policy*

Taken together, these findings suggest a differentiated public policy sequence according to level of development. In low-income economies, evidence of an absorptive-capacity threshold implies that expanding tertiary enrollment alone, without concurrent investment in basic connectivity and institutional strengthening, is unlikely to translate into greater AI readiness; the sequencing of intervention matters as much as its magnitude. In middle- and high-income economies, where most of Latin America is situated, by contrast, sustained investment in higher education emerges as a public policy lever with a demonstrable return on institutional AI readiness, reinforcing the case for strengthening higher education systems as an explicit component of national artificial intelligence strategies, beyond their intrinsic value for human development.

## 6. Limitations

This study presents limitations that should temper the interpretation of its findings. First, the cross-sectional design precludes establishing causality; the observed association between tertiary enrollment and AI readiness is compatible with alternative explanations, including the possibility that both are products of an unmodeled third institutional factor, or that governments with greater institutional readiness in turn invest more in higher education (reverse causality). Second, gross tertiary enrollment is a coarse proxy for the human capital relevant to AI: it does not capture educational quality, disciplinary orientation toward STEM fields, or the specific digital competencies of faculty or graduates, dimensions that future studies using primary data could incorporate. Third, listwise deletion reduced the analytic sample from 194 to 158 countries, and the excluded countries were not random; they were concentrated among microstates and economies with lower-capacity national statistical systems, which may have introduced a bias toward economies with greater statistical capacity, generally those of middle and high income. Fourth, the AI readiness index constitutes a composite measure whose validity depends on the methodological choices of the organization that constructs it; its strict comparability with earlier editions is not guaranteed, which is why this study deliberately limited itself to a cross-section of the most recent available year. Fifth, the VIF diagnostic indicated moderate collinearity between the logarithm of GDP per capita and the other predictors, warranting additional caution in interpreting the individual coefficients of the additive model beyond their joint statistical significance. Finally, because the unit of analysis is the country, these findings should not be extrapolated to higher education institutions, academic programs, or specific individuals, in order to avoid an ecological fallacy.

## 7. Conclusion and Implications

This study shows that the formation of human capital through higher education contributes significantly and independently to explaining governments' institutional readiness for artificial intelligence, beyond what national income and digital infrastructure predict. This return is not uniform, however: it dissipates in low-income countries, where more elementary structural constraints appear to limit the capacity to translate human capital into institutional capacity, a pattern consistent with the literature on absorptive capacity and technological catch-up. For public policy formulation, these results suggest that national AI readiness strategies in low-income economies require, as a precondition or concurrent measure, investment in basic infrastructure and institutional strengthening, without which the expansion of higher education alone may fail to translate into governmental technological capacity. In middle- and high-income economies, by contrast, sustained investment in higher education emerges as a public policy lever with a demonstrable return on institutional AI readiness, a finding with direct implications for the Latin American region, where educational human capital appears, on average, to be underutilized relative to its potential for translation into institutional capacity. Future research should incorporate indicators of educational quality and STEM orientation, explore causal directionality through longitudinal or instrumental-variable designs, and examine whether this threshold pattern is replicated at the subnational level in large federal countries.

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