

Government AI Readiness and Formal Entrepreneurship: A Cross-Country Analysis of New Business Density

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ABSTRACT

Government artificial intelligence (AI) readiness is increasingly used to benchmark national digital capacity, but its relationship with formal entrepreneurship remains unclear. This study examines the cross-country association between public-sector AI readiness and new business density across 156 countries. Using the Oxford Insights Government AI Readiness Index 2025 and World Bank indicators mainly from 2022, the analysis treats AI readiness as a contemporary proxy for persistent digital-governance capacity rather than as a temporal or causal predictor. OLS estimates with HC3 robust standard errors show that government AI readiness is positively associated with log new business density after controlling for GDP per capita, internet use, population size, and urbanisation ($\beta = 0.032$, $p = .002$). The association weakens when tertiary enrolment is added, suggesting that AI readiness overlaps with broader human-capital conditions. A robustness check using self-employment produces a different pattern, reinforcing the distinction between formal business entry and necessity-based entrepreneurship. The findings indicate that government AI readiness forms part of the institutional and digital environment associated with formal business formation, but its relevance cannot be separated from education, development, and administrative capacity.

Introduction

Formal entrepreneurship is shaped not only by individual initiative but also by the institutional and digital environment created by the state. The decision to register a business depends on administrative procedures, regulatory predictability, access to information, and the cost of entering the formal economy. Earlier cross-country research has shown that entry regulation and institutional quality matter for new firm formation (Djankov et al., 2002; Klapper et al., 2010; North, 1990; van Stel et al., 2007). More recent entrepreneurship research extends this view by treating business formation as embedded in national systems and wider ecosystem conditions rather than as an isolated individual choice (Acs et al., 2014; Stam, 2015; Wurth et al., 2022).

The digital transformation of government adds a newer layer to this environment. Digital public services, interoperable data systems, and transparent online procedures may reduce the informational and administrative frictions faced by potential entrants. Digital entrepreneurship research has shown that digital technologies reshape opportunity recognition, experimentation, scaling, and market access (Autio et al., 2018; Nambisan et al., 2019). Yet these effects are not evenly distributed across countries. They depend on the institutional and infrastructural conditions under which entrepreneurs interact with markets and public agencies.

Existing cross-country work often captures the digital context through broad ICT indicators, especially internet penetration. These measures are useful, but they mainly tell us whether citizens and firms are connected. They say less about whether the state has the data infrastructure, regulatory capacity, and administrative systems needed to support a predictable digital business environment. Government AI readiness offers a way to observe this state-level digital capacity. In this paper, AI readiness is not treated as a measure of firm-level AI adoption. It is treated more cautiously as a proxy for national digital-governance capacity, reflecting public-sector preparedness in areas such as data infrastructure, strategy, governance, and operational capability (Oxford Insights, 2025). This interpretation is consistent with recent AI-preparedness research, which emphasises that countries' ability to benefit from AI depends on digital infrastructure, human capital, innovation systems, and regulatory capacity (Cazzaniga et al., 2024).

This study examines whether countries with higher government AI readiness also display higher levels of formal entrepreneurship. The analysis combines the Oxford Insights Government AI Readiness Index 2025 with World Bank indicators for 156 countries. The main dependent variable is the natural logarithm of new business density, based on newly registered limited-liability firms relative to population. This indicator is widely used as a comparable measure of formal business entry across countries (World Bank, 2023). The empirical models control for GDP per capita, internet use, population size, and urbanisation, allowing the analysis to assess whether the AI-readiness association remains visible after major development and digital-access factors are considered.

The study is deliberately framed as a cross-country association rather than a causal test. This caution is necessary because government AI readiness is closely related to broader national development, institutional quality, human capital, and digital infrastructure. It is also necessary for temporal reasons: the AI-readiness indicator is measured in 2025, whereas the entrepreneurship and control variables used in the core analysis are primarily from 2022. The analysis therefore should not be read as evidence that AI readiness in 2025 causes earlier business formation. Instead, the index is used as a contemporary proxy for relatively persistent national digital-governance capacity, and the estimates are interpreted as structural cross-country associations.

The results show that government AI readiness is positively associated with log new business density. This association remains statistically significant in the preferred model after controlling for GDP per capita, internet use, population size, and urbanisation. However, the relationship is not mechanical. The coefficient weakens when tertiary enrolment is added, suggesting overlap with broader human-capital conditions, and the pattern differs when self-employment is used as an alternative outcome. This distinction matters because self-employment often reflects necessity entrepreneurship rather than formal opportunity-oriented entry (Baumol, 1990; Wennekers & Thurik, 1999).

The paper contributes to the literature in two ways. First, it shifts the discussion of digital entrepreneurship from basic ICT access towards state-level digital-governance capacity. Rather than asking only whether internet use is related to entrepreneurship, it asks whether governments that appear better prepared for advanced digital technologies are also located in countries with higher formal business formation. Second, it provides a boundary condition to technology-centred policy narratives: AI readiness is associated with formal entrepreneurship, but this association is embedded in wider educational, institutional, and developmental conditions. The remainder of the paper reviews the

literature, describes the data and methods, presents the results, and discusses the implications and limitations.

2. Literature Review

2.1 Institutions, Digital Capacity and Formal Business Formation

Formal business formation depends on the institutional conditions under which firms enter the formal economy. Rules, administrative quality, and regulatory predictability structure the incentives facing economic actors (North, 1990). Cross-country evidence also shows that entry regulation and administrative barriers shape new firm registration and early-stage entrepreneurial activity (Djankov et al., 2002; Klapper et al., 2010; van Stel et al., 2007). New business density therefore captures more than entrepreneurial activity alone; it also reflects how accessible and administratively manageable the formal economy is for potential entrants.

Entrepreneurial ecosystem research extends this logic by treating entrepreneurship as embedded in wider national and relational systems rather than as an isolated individual choice. National systems of entrepreneurship emphasise how country-level institutions filter individual opportunity pursuit into productive entrepreneurial outcomes (Acs et al., 2014). Similarly, entrepreneurial ecosystems are better understood as configurations of markets, knowledge resources, support organisations, social relations, and regulatory arrangements (Spigel, 2017; Stam, 2015; Wurth et al., 2022). New business density does not measure the whole ecosystem, but it offers a comparable observable outcome: the rate at which new limited-liability firms are formally registered. This metric differs from self-employment, which may reflect necessity-driven labour market activity rather than formal opportunity-oriented entrepreneurship. Formal business registration is therefore the more suitable primary outcome for this study.

Digitalisation adds another layer to this institutional environment. Digital public services, online registration systems, interoperable databases, and clearer information channels can reduce search costs and administrative friction for firms. Digital entrepreneurship research shows that digital technologies reshape opportunity recognition, experimentation, scaling, and market access (Autio et al., 2018; Nambisan et al., 2019; Sahut et al., 2021). Yet digital entrepreneurship cannot be reduced to connectivity alone. Digital entrepreneurial ecosystems link digital outputs, digital environments, platforms, institutions, users, and entrepreneurial actors within broader socio-technical conditions (Bejjani et al., 2023; Elia et al., 2020; Sussan & Acs, 2017).

This systemic view exposes a limitation in cross-country studies that rely mainly on internet penetration to capture the digital environment. Internet use indicates whether citizens and firms are connected; it says less about whether the state has the administrative systems, data infrastructure, regulatory capacity, and public digital services needed to make formal entry predictable. Since registration, compliance, and access to official information involve direct interaction with government, state-level digital capacity should be treated as part of the institutional environment surrounding formal entrepreneurship, not merely as another ICT control.

2.2 Government AI Readiness and Digital-Governance Capacity

Government AI readiness provides a contemporary proxy for state-level digital-governance capacity. The Oxford Insights Government AI Readiness Index assesses how prepared governments are to use and govern AI, drawing on dimensions such as public-sector strategy, data and infrastructure, technology capacity, and governance arrangements (Oxford Insights, 2025). In this study, AI readiness is not interpreted as evidence of firm-level AI adoption. It is used as a composite signal of public-sector preparedness to govern, coordinate, and deploy advanced digital technologies.

This interpretation is consistent with recent AI-preparedness research, which treats national AI capacity as dependent on digital infrastructure, human capital, innovation systems, and regulatory readiness (Cazzaniga et al., 2024; International Monetary Fund, 2024). Recent World Bank work similarly frames AI readiness around foundational digital capacity, including connectivity, computing resources, context-specific data, and competency in digital skills (World Bank, 2025). These dimensions overlap with the conditions that support formal business formation. Countries with stronger digital-governance capacity are more likely to have transparent public services, clearer data standards, coordinated regulatory systems, and more capable online administrative infrastructure. These conditions do not create entrepreneurs directly, but they can reduce frictions around formal registration and business operation.

The expected link between AI readiness and formal entrepreneurship is therefore indirect and institutional. AI readiness belongs to the wider digital and administrative environment in which new firms are created. The relevant channels operate through data transparency, regulatory predictability, and reduced bureaucratic delay. These mechanisms align with digital entrepreneurship research, where digital technologies generate entrepreneurial possibilities only when embedded in supportive institutional and infrastructural settings (Autio et al., 2018; Nambisan et al., 2019; Bejjani et al., 2023). Recent evidence on the AI divide also suggests that countries' AI preparedness reflects deeper structural capabilities rather than short-term technology adoption alone (Mandon & Roberts, 2025).

The relationship must still be treated cautiously. AI readiness overlaps with broader development conditions: richer countries tend to have stronger internet access, better education systems, larger innovation capacity, and more capable public institutions. Recent OECD work similarly warns that the transition to AI may deepen divides across places, sectors, and firms when digital and institutional capacities remain uneven (Kergroach & Héritier, 2025). A positive association between AI readiness and new business density may therefore partly reflect this wider development bundle. This concern motivates the empirical strategy, which controls for GDP per capita, internet use, population size, and urbanisation, and then introduces tertiary enrolment as a robustness check.

Finally, the type of entrepreneurship being measured matters. New business density captures formal business entry, whereas self-employment often reflects necessity entrepreneurship, particularly in lower-income economies. Baumol's (1990) distinction between productive and less productive entrepreneurship remains useful because not all entrepreneurial activity carries the same institutional meaning. The entrepreneurship-development relationship also varies with the form of entrepreneurship observed (Wennekers & Thurik, 1999). Accordingly, log new business density is used as the primary outcome, while self-employment is treated only as a contrasting robustness measure.

Taken together, the literature supports a restrained empirical expectation: countries with higher government AI readiness are likely to display higher levels of formal business formation, but this association should be understood as conditional on broader development, human-capital, and digital-governance conditions rather than as a direct causal effect.

3. Data and Methods

3.1 Data and Variables

This study uses a cross-country dataset integrating public-sector digital capacity, formal business formation, and macro-structural controls. The primary independent variable is the Government AI Readiness Score from the Oxford Insights Government AI Readiness Index 2025 (Oxford Insights, 2025). The index ranges from 0 to 100 and captures public-sector preparedness across dimensions related to government strategy, technology capacity, data infrastructure, and governance arrangements. In this analysis, the score is used as a macro-level proxy for national digital-governance capacity rather than as evidence of firm-level AI adoption.

The dependent variable is the natural logarithm of new business density, denoted as $\ln(\text{New Business Density})$. New business density is calculated from World Bank World Development Indicators as newly registered businesses (IC.BUS.NREG) per 1,000 population, using total population (SP.POP.TOTL) as the scaling denominator (World Bank, 2023). The logarithmic transformation is applied to reduce positive skewness and to allow coefficient estimates to be interpreted approximately as percentage differences in formal business density. This registry-based measure is preferred because it captures formal business entry more directly than broader labour-market measures such as self-employment.

The control variables are also drawn from the World Bank World Development Indicators, mainly for 2022 (World Bank, 2023). They include $\ln(\text{GDP per capita})$, internet users as a percentage of the population, $\ln(\text{population})$, and urban population share. These variables capture major structural confounders: national income, digital access, market scale, and agglomeration conditions. The intersection of the AI-readiness data and World Bank indicators yields a core sample of 156 countries. Variable definitions, indicator codes, and measurement years are reported in Table 1.

The timing of the data requires careful interpretation. Government AI readiness is measured in 2025, whereas the entrepreneurship and control variables used in the core analysis are primarily measured in 2022. The study therefore does not treat AI readiness as a lagged predictor of business formation. Instead, the index is used as a contemporary proxy for relatively persistent national digital-governance capacity. The empirical design maps structural cross-country association rather than temporal sequence or causal impact.

Table 1. Variable Definitions and Data Sources

Variable	Role	Definition	Source / Code	Year
Government AI Readiness Score	Independent variable	Overall country score on the Government AI Readiness Index, scaled from 0 to 100	Oxford Insights GAIRI	2025

Log(New Business Density)	Dependent variable	Natural log of new business registrations per 1,000 population	World Bank WDI: IC.BUS.NREG; SP.POP.TOTL	2022
Log(GDP per Capita PPP)	Control	Natural log of GDP per capita, PPP-adjusted current international dollars	World Bank WDI: NY.GDP.PCAP.PP.CD	2022
Internet Users (%)	Control	Percentage of population using the Internet	World Bank WDI: IT.NET.USER.ZS	2022
Log(Population)	Control	Natural log of total population	World Bank WDI: SP.POP.TOTL	2022
Urban Population (%)	Control	Percentage of population living in urban areas	World Bank WDI: SP.URB.TOTL.IN.ZS	2022
Tertiary Enrolment (%)	Robustness control	Gross tertiary school enrolment ratio	World Bank WDI: SE.TER.ENRR	2022
Self-Employment Rate (%)	Alternative dependent variable	Self-employed workers as a percentage of total employment	World Bank WDI: SL.EMP.SELF.ZS	2022

Note. The primary dependent variable is calculated from new business registrations and total population, then log-transformed. GDP per capita, population, and new business density are log-transformed to reduce skewness.

3.2 Empirical Strategy

The empirical analysis estimates a sequence of cross-sectional ordinary least squares (OLS) specifications. The preferred model is written as follows:

$$\begin{aligned} \ln(\text{New Business Density}_i) &= \alpha + \beta_1 \text{AI Readiness}_i + \beta_2 \ln(\text{GDP per Capita}_i) + \beta_3 \text{Internet Users}_i + \beta_4 \ln(\text{Population}_i) \\ &+ \beta_5 \text{Urban Population}_i + \varepsilon_i \end{aligned}$$

where i denotes country and ε_i is the error term. The parameter of interest is β_1 , which captures the conditional association between government AI readiness and formal business formation after accounting for major development and digital-access factors. Because the sample combines countries with unequal income levels, institutional capacities, and registration systems, all specifications use HC3 heteroskedasticity-robust standard errors.

The models are estimated sequentially. Model 1 estimates the bivariate association between AI readiness and $\ln(\text{New Business Density})$. Model 2 adds $\ln(\text{GDP per capita})$ and internet use to account for the most direct economic-development and connectivity confounds. Model 3 is the preferred specification; it further includes $\ln(\text{population})$ and urban population share to control for country scale and agglomeration conditions while preserving the full 156-country sample.

Two robustness checks assess the boundary conditions of the main association. Robustness A adds tertiary school enrolment SE. TER. ENRR as a human-capital control (World Bank, 2023). This variable is not included in the preferred model because it reduces the sample from 156 to 105 countries, but it helps evaluate whether the AI-readiness association overlaps with educational infrastructure. Robustness B replaces the dependent variable with the self-employment rate SL. EMP. SELF. ZS (World Bank, 2023).

This alternative outcome is interpreted as a contrasting measure because self-employment often captures necessity entrepreneurship rather than formal opportunity-oriented entry. Variance inflation factors are used to assess multicollinearity.

Throughout the analysis, the estimates are interpreted as conditional associations. The models adjust for several prominent confounders, but they cannot eliminate unobserved country-level histories, legal traditions, policy sequencing, or reverse relationships between state capacity and formal entrepreneurship. The analysis therefore avoids causal language and focuses on how AI-related digital-governance capacity co-varies with formal business formation across countries.

4. Results and Discussion

4.1 Descriptive Patterns

The descriptive analysis first examines whether government AI readiness and formal business formation move together before economic and structural controls are introduced. Table 2 reports the descriptive statistics and Pearson correlation matrix for the main variables. Across the 156-country sample, the Government AI Readiness Score ranges from 12.80 to 80.81, while $\ln(\text{New Business Density})$ ranges from -4.30 to 2.73. The correlation matrix shows that AI readiness is positively and significantly associated with log new business density ($r = .516, p < .001$). This baseline pattern indicates that countries with stronger public-sector digital capacity tend to report higher formal business registration density, consistent with institutional arguments that formal entry depends partly on the administrative and regulatory environment surrounding market participation (Djankov et al., 2002; Klapper et al., 2010).

Table 2. Descriptive Statistics and Correlations

<i>Panel A. Descriptive Statistics</i>						
Variable	N	Mean	SD	Min	Median	Max
AI Readiness Score	156	45.882	18.549	12.800	43.845	80.810
New Business Density	156	2.318	2.878	0.014	1.303	15.278
Log(New Business Density)	156	-0.011	1.546	-4.299	0.264	2.726
Log(GDP per Capita PPP)	156	9.742	1.150	7.105	9.900	11.898
Internet Users (%)	156	70.097	25.238	9.637	78.713	100.000
Log(Population)	156	15.857	2.049	10.599	16.102	21.078
Urban Population (%)	156	60.686	21.640	14.736	61.927	100.000
Tertiary Enrolment (%)	105	57.382	29.797	5.322	57.816	166.390
Self-Employment Rate (%)	147	38.840	26.116	0.860	32.127	91.339

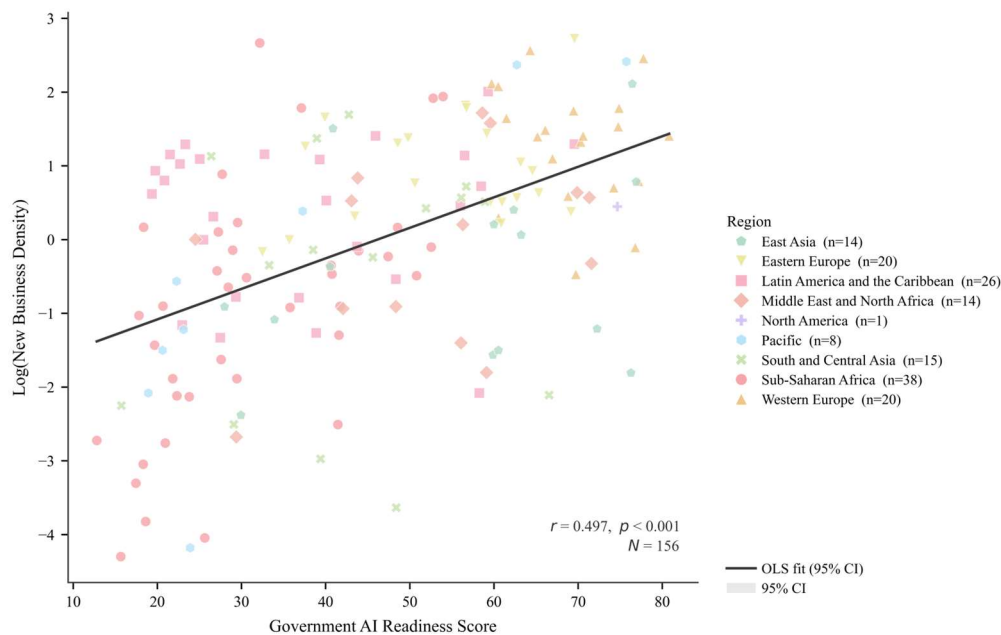
<i>Panel B. Pearson Correlations</i>							
Variable	1	2	3	4	5	6	7
1. AI Readiness	1.000						
2. Log(New Business Density)	0.516***	1.000					
3. Log(GDP per Capita PPP)	0.767***	0.698***	1.000				

4. Internet Users (%)	0.695***	0.653***	0.905***	1.000			
5. Log(Population)	0.341***	-0.352***	-0.143+	-0.165*	1.000		
6. Urban Population (%)	0.616***	0.500***	0.720***	0.724***	0.008	1.000	
7. Self-Employment Rate (%)	-0.633***	-0.679***	-0.864***	-0.863***	0.249**	-0.657***	1.000

Note. Panel A uses available observations. Panel B reports Pearson correlations using listwise deletion, $N = 147$. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Figure 1 visualises the same bivariate relationship using the full available sample for AI readiness and log new business density. The fitted line slopes upward, with a positive correlation ($r = .497, p < .001, N = 156$). This value differs slightly from the Table 2 correlation because the correlation matrix uses listwise deletion across variables ($N = 147$), whereas Figure 1 uses the full pairwise sample for the two plotted variables. The difference is therefore a sample-construction issue rather than a substantive inconsistency; both estimates point to a positive association. At the same time, the wide dispersion of country observations confirms that AI readiness alone cannot explain cross-country variation in formal business formation.

Figure 1. Government AI Readiness and New Business Density



The correlation matrix also shows why this association cannot be interpreted in isolation. AI readiness is strongly correlated with $\ln(\text{GDP per capita})$ ($r = .767$) and internet use ($r = .695$), indicating that it is closely tied to broader development conditions rather than functioning as a stand-alone technology variable. Recent AI-preparedness frameworks make a similar point: national AI capacity depends on digital infrastructure, human capital, innovation systems, and legal or regulatory readiness (Cazzaniga et al., 2024; International Monetary Fund, 2024). The empirical question is

therefore whether the AI-readiness association remains visible after major development and connectivity conditions are considered.

The descriptive evidence further supports the distinction between formal business registration and self-employment. AI readiness is negatively correlated with self-employment ($r = -.633$), while self-employment is also negatively related to income and internet use. This pattern is consistent with the distinction between formal opportunity-oriented entry and necessity-based self-employment (Baumol, 1990; Wennekers & Thurik, 1999). New business density is therefore retained as the primary outcome, while self-employment is used only as a contrasting robustness measure.

4.2 Main Regression Results

Table 3 presents the OLS estimates for the main specifications and the education robustness model. Model 1 confirms the descriptive relationship: AI readiness is positively and significantly associated with log new business density ($\beta = 0.041$, $p < .001$). Because the dependent variable is log-transformed, this coefficient can be read as an approximate semi-elastic association: a one-point higher AI Readiness Score is associated with about 4.1% higher new business density before controls are added.

Table 3. OLS Estimates for New Business Density

Variable	Model 1	Model 2	Model 3	Robustness A
AI Readiness Score	0.041*** (0.006)	-0.004 (0.007)	0.032** (0.010)	0.022 (0.014)
Log(GDP per Capita PPP)		0.998*** (0.231)	0.659* (0.335)	0.419 (0.359)
Internet Users (%)		-0.000 (0.010)	-0.008 (0.012)	0.003 (0.014)
Log(Population)			-0.293*** (0.081)	-0.295** (0.108)
Urban Population (%)			0.001 (0.007)	0.002 (0.010)
Tertiary Enrolment (%)				0.004 (0.006)
Constant	-1.910*** (0.325)	-9.537*** (1.593)	-2.745 (3.272)	-0.932 (3.872)
Observations	156	156	156	105
R ²	0.247	0.497	0.560	0.493
Adjusted R ²	0.242	0.487	0.545	0.462

Note. HC3 robust standard errors are reported in parentheses. Model 3 is the preferred specification. Robustness A adds tertiary enrolment; the sample falls to 105 countries because of missing education data. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

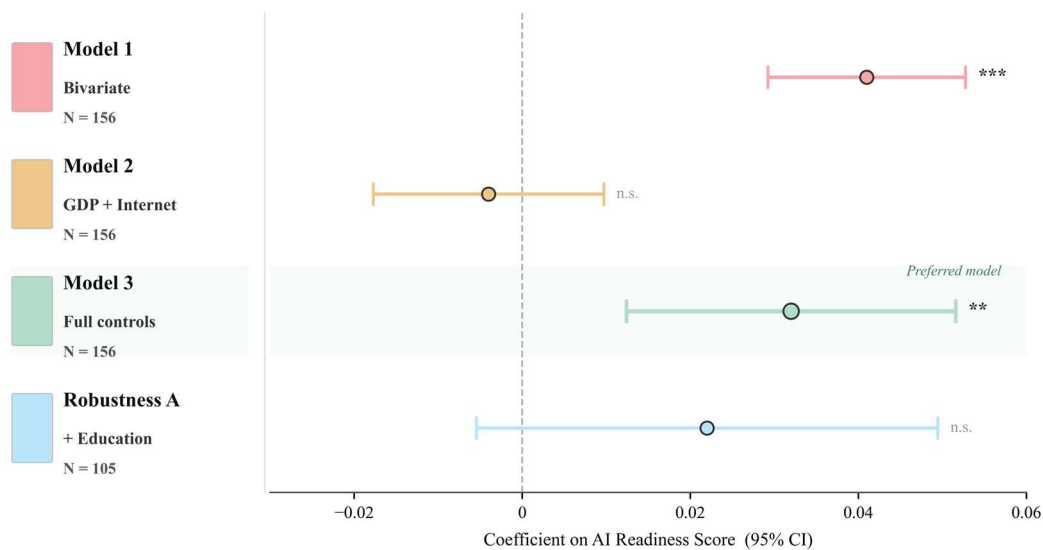
Model 2 adds $\ln(\text{GDP per capita})$ and internet use. At this stage, the AI-readiness coefficient becomes negative and statistically insignificant. This reversal should not be interpreted as evidence that AI readiness is harmful to formal entrepreneurship. A more plausible reading is that AI readiness shares substantial variance with income and digital connectivity. Digital entrepreneurship research increasingly

treats technologies, institutions, platforms, and infrastructure as mutually embedded rather than independent forces (Autio et al., 2018; Bejjani et al., 2023; Nambisan et al., 2019).

Model 3, the preferred specification, adds $\ln(\text{population})$ and urban population share. Once country scale and urbanisation are included, the AI-readiness coefficient becomes positive and statistically significant again ($\beta = 0.032, p = .002$), with the model explaining 56.0% of the cross-country variation in log new business density. This pattern suggests that the AI-readiness association becomes clearer only after accounting for both development level and country-structure conditions. Population size and urbanisation capture important differences in market scale, agglomeration, and the administrative setting in which formal registration occurs. The result therefore supports a conditional interpretation: digital-governance capacity may matter for formal business formation, but only within broader institutional and demographic contexts.

Figure 2 summarises the estimated AI-readiness coefficients across the main specifications and Robustness A. The coefficient is positive and significant in the bivariate model, becomes statistically insignificant after adding GDP per capita and internet use, and returns to a positive significant association in the preferred full-control model. The figure also shows that the confidence interval widens and crosses zero when tertiary enrolment is added, reflecting the smaller sample and the overlap between AI readiness and human-capital conditions.

Figure 2. AI Readiness Coefficients across Model Specifications



Note: Points show AI-readiness coefficients; bars show 95% CIs using HC3 robust SEs.
DV = Log(New Business Density). ** $p < 0.01$, *** $p < 0.001$.

This result should still be read as a conditional association, not as evidence of an independent causal effect. Countries with stronger AI readiness are also countries where formal business formation is more prevalent after several major controls are included. This interpretation is consistent with entrepreneurial ecosystem research, which treats entrepreneurship as embedded in institutional, infrastructural, and policy conditions rather than as an isolated individual act (Stam, 2015; Wurth et al., 2022).

4.3 Robustness, Diagnostics and Interpretation

Table 4 reports the robustness checks and diagnostic results. Robustness A adds tertiary enrolment as a human-capital control. The AI-readiness coefficient remains positive but becomes statistically insignificant, while the sample falls from 156 to 105 countries because of missing education data. This result should not be read simply as a failed robustness test. Instead, it indicates that public-sector AI readiness is closely intertwined with the human-capital base that allows digital administrative capacity to become economically meaningful. AI readiness is therefore unlikely to support formal business formation through digital infrastructure alone; it appears to operate alongside education systems, technical skills, and broader institutional development. This interpretation aligns with AI-preparedness frameworks that place human capital alongside infrastructure and regulation as a core condition of national AI capacity (Cazzaniga et al., 2024; International Monetary Fund, 2024).

Table 4. Robustness Checks and Diagnostics

<i>Panel A. Multicollinearity Diagnostics for Model 3</i>		
Variable		VIF
AI Readiness Score		5.10
Log(GDP per Capita PPP)		7.07
Internet Users (%)		5.61
Log(Population)		2.44
Urban Population (%)		2.18
<i>Panel B. Alternative Dependent Variable: Self-Employment Rate</i>		
Variable	Robustness B1	Robustness B2
AI Readiness Score	-0.909*** (0.083)	-0.148 (0.147)
Controls	No	Yes
Observations	147	147
R ²	0.401	0.797

Note. Panel A reports VIF values for the preferred model. Panel B uses self-employment rate as the alternative dependent variable. Robustness B2 includes the full Model 3 controls. HC3 robust standard errors are reported in parentheses. + $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$.

The multicollinearity diagnostics reinforce this cautious reading. The maximum VIF in the preferred model is 7.07, below the common threshold of 10 but still indicating moderate overlap among predictors. This overlap is not merely a statistical inconvenience; it reflects the substantive reality that AI readiness, income, internet access, education, and administrative capacity tend to develop together. The diagnostics therefore support the decision to avoid causal claims and interpret the estimates as conditional cross-country associations.

Robustness B replaces log new business density with the self-employment rate. The bivariate association between AI readiness and self-employment is negative and statistically significant, but the coefficient becomes insignificant under the full controls. This divergent pattern strengthens the paper's measurement argument. Self-employment often reflects necessity-based labour-market activity, especially in lower-income economies, whereas new business density captures formal entry into the registered economy. The result therefore does not contradict the main finding; it shows that different entrepreneurship indicators capture different institutional realities.

Taken together, the results indicate that government AI readiness is positively associated with formal business formation in the preferred model, but the association is conditional. It is strongest when entrepreneurship is measured as formal new business registration, weaker when education is added, and absent when self-employment is used as the outcome under full controls. For policy, the implication is cautious: investments in AI strategy, data governance, and digital public capacity may complement formal business formation, but they are unlikely to substitute for education, institutional quality, and broader administrative capacity. This interpretation fits recent digital-government and digital-public-infrastructure debates, which emphasise that public digital systems matter most when embedded in wider governance capacity (OECD, 2025; World Bank, 2024).

5. CONCLUSION

This study examined the cross-country relationship between government artificial intelligence (AI) readiness and formal entrepreneurship. Using the Oxford Insights Government AI Readiness Index 2025 and World Bank indicators for 156 countries, the analysis focused on $\ln(\text{New Business Density})$ as a measure of formal business registration. The study positioned AI readiness as a proxy for national digital-governance capacity and interpreted the estimates as structural cross-country associations rather than causal effects.

The results show that countries with higher government AI readiness tend to report higher formal business registration density. In the preferred model, this association remains positive after controlling for GDP per capita, internet use, population size, and urbanisation. This suggests that AI readiness captures more than basic digital connectivity. It is also linked to the broader public-sector environment in which firms access information, interact with regulatory systems, and enter the formal economy. At the same time, the robustness checks place clear boundaries around this interpretation. The association weakens when tertiary enrolment is added, and it does not extend to self-employment under full controls. These patterns indicate that AI readiness is closely tied to human-capital and institutional conditions, while formal business registration should not be treated as equivalent to necessity-based self-employment.

The main contribution of the paper is to bring state-level digital-governance capacity into the institutional analysis of formal business formation. Much of the digital entrepreneurship literature focuses on connectivity, platforms, or firm-level technology use. This study shifts the lens towards the digital capacity of the public sector and shows that government AI readiness is systematically associated with formal entry across a broad cross-country sample. The evidence supports a restrained conclusion: AI readiness may form part of the enabling environment for formal entrepreneurship, but it is not an institutional shortcut around education, administrative quality, or broader development conditions.

Several boundaries remain. The cross-sectional design cannot establish temporal order, especially because AI readiness is measured in 2025 while the entrepreneurship and control variables are primarily from 2022. Future research should use longitudinal data to examine whether improvements in digital public capacity precede later changes in formal business formation. New business density also captures registration rather than firm survival, employment growth, innovation, or productivity. Further work using firm-level or sector-specific data could test whether AI readiness is more strongly related to higher-

quality entrepreneurial outcomes. Finally, the composite nature of the AI-readiness index leaves open which dimensions—data infrastructure, government strategy, regulatory capacity, or technology-sector conditions—matter most.

For policy, the implication is one of complementarity. Public investment in AI strategy, data governance, and digital administrative capacity may support a more favourable environment for formal business entry, particularly where it reduces information and compliance frictions. This interpretation is consistent with recent digital and AI policy work that treats connectivity, data systems, digital public infrastructure, skills, and safeguards as mutually reinforcing components of digital development (World Bank, 2025). Such investment is unlikely to work in isolation. The findings suggest that AI readiness is most meaningful when embedded in a wider state-capacity agenda that also includes education, institutional reliability, and effective public administration.

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