

Does AI Readiness Promote Financial Development? Evidence On Institutional Complementarity

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ABSTRACT: This study examines whether national artificial intelligence (AI) readiness translates into financial development and whether institutional quality conditions that relationship. The Government AI Readiness Index produced by Oxford Insights is matched with the World Development Indicators and Worldwide Governance Indicators to construct a panel of 193 economies and 894 country-year observations for 2020-2024. The empirical design combines country and year fixed effects with a Mundlak correlated-random-effects decomposition, transmission-channel tests, and marginal-effect estimates for interaction models. A one-standard-deviation increase in AI readiness is associated with a 4.250-percentage-point increase in bank credit to the private sector as a share of gross domestic product (GDP). Formal entrepreneurship, labor productivity, and structural upgrading exhibit three positive transmission patterns. The central result is conditional: the marginal association between AI readiness and financial development is statistically insignificant when institutional quality is low, positive at the median, and strongest when institutional quality is high. Alternative variables, sample restrictions, fixed-effect structures, limited-instrument system generalized method of moments (GMM), and fixed-effects instrumental-variable estimates support the same pattern under their respective assumptions. The findings frame AI readiness as deployable technological capacity and institutional quality as the condition that converts this capacity into credible, enforceable, and scalable financial activity.

KEYWORDS: Artificial Intelligence Readiness; Financial Development; Institutional Quality; Formal Entrepreneurship; Labor Productivity; Structural Upgrading

JEL CLASSIFICATION: G20; O16; O33; C23

I. LITERATURE REVIEW

A. National AI Readiness and Financial Development

Government AI readiness measures an economy's capacity to adopt, deploy, and govern AI for the public interest. The Oxford Insights index comprises three pillars: government capacity, the technology sector, and data and infrastructure. It therefore differs from realized firm-level AI use, AI patents, or fintech adoption. AI readiness captures the enabling environment for deployment (Iuga & Socol, 2024; Nzobonimpa & Savard, 2023; Davidson, 2024). This distinction is central because the relevant issue is the distance between technological capacity and realized application.

AI can promote financial deepening along several margins. More accurate screening can reduce adverse selection, automated processing can lower the fixed cost per account, fraud detection can strengthen trust, and digital interfaces can overcome the geographic limits of physical branches. These applications provide a microeconomic basis for expecting a positive aggregate association between AI and financial development (Mhlanga, 2020; Pattnaik et al., 2024; Bahoo et al., 2024). Yet financial development also depends on savings, macroeconomic stability, competition, legal enforcement, and demand for formal finance. AI readiness should therefore be understood as enabling capacity rather than as a treatment that mechanically produces financial outcomes.

The outcomes in this study measure financial depth. Bank credit to the private sector captures the intermediation depth of deposit-taking institutions; total credit to the private sector covers a broader set of lenders; and broad money reflects the scale of liquid financial claims. A composite indicator reduces dependence on any single balance-sheet measure. These outcomes differ from multidimensional financial-inclusion measures that combine availability, access, and use (Omar & Inaba, 2020). The study therefore asks whether AI readiness is associated with the scale of formal financial intermediation, not whether every expansion is necessarily safer, more equitable, or more efficient.

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The available evidence makes a positive association plausible but remains incomplete. Firm-level research links AI innovation to productivity, while cross-country work associates AI patents with economic growth (Czarnitzki et al., 2023; Gonzales, 2023). Patents, firm adoption, fintech use, and government AI readiness, however, operate at different levels and change at different rates. Over a short panel, annual variation in AI readiness must therefore be distinguished from accumulated national capabilities rather than treated as a single homogeneous source of variation.

B. Institutional Complementarity and Real-Economy Transmission Channels

Institutions influence financial development because property rights, disclosure, contract enforcement, regulatory quality, and public integrity jointly determine whether financial claims are credible. Weak legal and governance environments constrain external finance, especially for smaller firms (La Porta et al., 1997; Beck et al., 2005). AI introduces additional institutional requirements because automated decisions depend on access to data, cybersecurity, model oversight, and coordination between public and private actors. Government effectiveness can coordinate standards and infrastructure; regulatory quality can support innovation without abandoning prudential oversight; and the rule of law and control of corruption can protect digital records from arbitrary interference.

These relationships imply complementarity between institutions and technology. In stronger institutional environments, the same technological capacity can support broader data use, more reliable verification, and financial services at greater scale. In weaker environments, AI readiness may remain concentrated in public demonstration projects or a small number of firms. Automation could theoretically substitute for limited administrative capacity, but the stronger expectation is that institutions and technological readiness reinforce one another. The institutional interaction is therefore the central boundary condition in this study.

Formal entrepreneurship provides the first transmission channel. AI can reduce the cost of market analysis, product design, customer acquisition, and administration, thereby supporting the creation and expansion of formal firms (Chalmers et al., 2021; Gofman & Jin, 2024). A larger formal business sector increases demand for bank accounts, payments, working capital, and external finance. Because financial development may also encourage entrepreneurial entry, the evidence is interpreted as a transmission pattern rather than as a uniquely identified causal chain.

Labor productivity provides the second channel. AI can automate codifiable tasks, improve forecasting, and complement skilled labor, although productivity gains still depend on organizational restructuring and human capital (Zirar et al., 2023; Czarnitzki et al., 2023). Higher productivity can increase income, savings, investment, and repayment capacity, thereby supporting financial deepening. Structural upgrading provides a third channel: the movement of economic activity toward information-intensive and service sectors raises transaction frequency and demand for formal financial intermediation. The service-sector share is an imperfect proxy, so it is interpreted as sectoral reallocation rather than a complete development ladder.

II. INTRODUCTION

Financial systems connect savings with investment, support business financing, and allocate resources. Their development therefore shapes both real economic growth and macroeconomic stability (King & Levine, 1993; Beck et al., 2005). Artificial intelligence is a general-purpose technology that is reshaping financial intermediation through automated screening, credit assessment, fraud detection, customer service, and risk monitoring. Compared with conventional information technology, AI depends more heavily on high-quality data, digital infrastructure, specialized skills, and credible governance; its economic effects are not determined by technological availability alone. At the national level, whether AI can be widely deployed and translated into financial development depends not only on the technology sector and infrastructure but also on government coordination, regulatory capacity, contract enforcement, and data governance. Understanding how national AI readiness translates into financial development, and whether institutional quality conditions that process, is therefore important for both theory and policy.

Existing research on AI and its economic consequences falls into several related strands. The first examines applications in banks and other financial institutions and shows that intelligent screening, risk assessment, customer support, and fraud detection can mitigate information asymmetry and lower the cost of financial services (Mhlanga, 2020; Pattnaik et al., 2024; Bahoo et al., 2024). The second studies real-economy effects through productivity and organizational capabilities, emphasizing that AI yields productivity gains only when it complements human and organizational capital (Czarnitzki et al., 2023; Parteka & Kordalska, 2023; Zirar et al., 2023). A third strand shows that financial development depends on property-rights protection, contract enforcement, governance, and institutional credibility, and that the expansion of digital finance is likewise conditioned by regulatory and institutional environments (La Porta et al., 1997; Chinoda & Kapingura, 2024; Jin et al., 2024). The study closest to the present paper examines the joint effect of government AI readiness and the rule of law on anti-money-laundering risk, but its outcome is financial-integrity risk rather than the scale and depth of financial intermediation (Kirichok et al., 2025). Overall, prior research

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primarily explains the direct application effects of AI or the general effects of institutions on finance. It pays less attention to the more fundamental question of how national technological readiness becomes financial development and why countries with similar AI readiness may achieve different financial outcomes.

The literature leaves four related gaps. First, most studies interpret the financial implications of AI through application, automation, or efficiency, without separating the capacity to deploy technology from the realization of economic outcomes. This makes it difficult to explain why stronger AI readiness does not necessarily coincide with a deeper financial system. Institutional complementarity provides a useful perspective: AI readiness represents potential technological capacity, whereas institutional quality determines whether that capacity can support credible, enforceable, and scalable financial activity. Second, the literature treats entrepreneurship, productivity, and industrial structure largely as separate mechanisms rather than as parts of a common conversion process. Third, national AI readiness is persistent, so short-run within-country changes and long-run cross-country capability differences represent distinct estimands. A single panel model can blur these dimensions. Finally, an interaction coefficient alone does not reveal how the marginal association of AI readiness varies across levels of institutional quality.

This study addresses these gaps by asking whether national AI readiness is positively associated with financial development, whether formal entrepreneurship, labor productivity, and structural upgrading exhibit transmission patterns consistent with that association, and whether institutional quality strengthens it. The theoretical contribution is to move from a direct technology-effect perspective to an institutional-conversion framework that explains why countries with comparable technological capacity may realize different financial outcomes. The three real-economy channels are integrated within this framework, while institutional quality is treated as a boundary condition for converting technological capacity into financial deepening. Empirically, the study uses a cross-country panel for 2020-2024. Country and year fixed effects identify annual within-country variation, while a Mundlak correlated-random-effects model separates within-country change from persistent between-country differences. The moderation analysis reports marginal effects at different levels of institutional quality, and robustness, endogeneity, and heterogeneity tests assess the stability of the main pattern. The mechanism and moderation estimates are interpreted as conditional associations; contemporaneous pathway estimates do not establish a causal mediation chain.

Table 1. Comparison with the Closest Empirical Studies

Study	Sample	Measure of AI	Outcome	Institutional condition	Increment of this study
Gonzales (2023)	165 countries; 1970-2019 in five-year periods	AI patents	Real GDP per capita growth	None	Uses fixed effects, Anderson-Hsiao, and GMM and establishes a precedent for research on AI innovation and growth, but does not examine AI readiness or financial development.
Omar and Inaba (2020)	116 developing countries; 2004-2016	None	Financial inclusion, poverty, and income inequality	Institutions enter as conditioning variables, not as moderators of AI readiness	Uses an annual panel and fixed effects and establishes a precedent for multidimensional financial outcomes, but does not incorporate AI capacity.
Kirichok et al. (2025)	Up to 168 countries; 2020-2024	Government AI readiness	Basel anti-money-laundering risk	Interaction with the rule of law	Uses fixed and random effects and is closest in its explanatory and moderating variables, but examines financial integrity rather than financial depth.
This study	Unified panel of 193 economies; 2020-2024; model-specific estimation samples	Government AI readiness and the Data and Infrastructure pillar	Bank credit, private-sector credit, broad money, and a fixed-component financial-depth index	Interaction with a four-dimensional Worldwide Governance Indicators (WGI) composite	Uses two-way fixed effects and a within-between decomposition; links AI readiness to financial depth and interprets moderation as a hierarchical conditional association.

III. THEORETICAL ANALYSIS AND HYPOTHESES

A. AI Readiness and Financial Development

National AI readiness captures the digital infrastructure, data resources, technology sector, specialized skills, and administrative capabilities required to deploy and govern AI at scale. Its contribution to financial development does not arise simply from more technological equipment. It arises when those capabilities complement financial-intermediation activities and improve information processing and service delivery. Machine learning, big-data analytics, and automation can help financial institutions identify borrowers, assess credit risk, and detect anomalous transactions, thereby mitigating information asymmetry. Intelligent customer service, remote identity verification, and automated processing can lower the marginal cost of serving individual customers and reduce the geographic constraint imposed by physical branches (Mhlanga, 2020; Pattnaik et al., 2024; Bahoo et al., 2024). AI readiness may also improve productive efficiency and increase demand by firms and households for payments, savings, credit, and risk-management services. It can thus expand financial services through both supply-side capacity and real-economy demand.

H1. National AI readiness is positively associated with financial development.

B. Real-Economy Transmission Channels

Formal entrepreneurship is an important channel through which AI readiness may be associated with financial development. AI can lower entrepreneurs' costs of obtaining market information, identifying opportunities, designing products, and completing administrative tasks, improving both business formation and operations (Chalmers et al., 2021). A stronger AI knowledge base, a larger pool of technical talent, and better digital infrastructure also create a more favorable environment for new firms and can encourage activity to move from informal to formal sectors (Gofman & Jin, 2024). As more firms register, transact, and expand through formal channels, their demand for bank accounts, payment settlement, working capital, credit, and risk-management services rises. A larger formal business sector also expands the customer base that financial institutions can identify, verify, and serve on a sustained basis.

H2a. AI readiness is positively associated with financial development through greater formal entrepreneurship.

Labor productivity is a second transmission channel. By combining machine learning, intelligent forecasting, and process automation, AI can replace some repetitive tasks while complementing skilled workers, organizational capital, and firm-specific knowledge. This combination can improve information processing, resource allocation, and decision efficiency (Czarnitzki et al., 2023; Zirar et al., 2023). When those complementarities raise labor productivity, firms may improve output, profitability, and internal accumulation, expanding productive investment and demand for external finance. Productivity gains may also support household income and saving, strengthen borrowers' repayment capacity, and improve lenders' risk expectations. AI readiness may therefore deepen finance by reinforcing both demand and supply conditions.

H2b. AI readiness is positively associated with financial development through higher labor productivity.

Structural upgrading may provide a third channel. Accumulation of data, computing capacity, digital networks, and AI skills can shift activity from traditional agriculture and low-value-added production toward information-, technology-, and service-intensive sectors. Compared with traditional sectors, producer services, communications, logistics, digital trade, and professional services involve more frequent transactions, more complex information, and greater cross-regional resource allocation. They consequently depend more heavily on formal payment, credit, insurance, and risk-management infrastructure. AI readiness can support the expansion of these sectors and improve information links and resource matching across industries. As the service share rises and economic structure upgrades, the range of intermediation and the scale of financial balance sheets may expand.

H2c. AI readiness is positively associated with financial development through structural upgrading.

C Moderating Role of Institutional Quality

Whether AI readiness translates into financial development also depends on the institutional environment in which technological capacity is embedded. Financial activity rests on property-rights protection, contract enforcement, disclosure, and credible regulation. La Porta et al. (1997) show that sound legal institutions and investor protection are important for external finance, while Beck et al. (2005) demonstrate that governance and institutional conditions affect firms' access to financial resources. Institutions are especially important for finance based on data and algorithms. Government effectiveness supports digital infrastructure and coordination; regulatory quality provides stable expectations while containing financial risk; the rule of law helps enforce digital contracts and financial claims; and control of corruption reduces arbitrary intervention in data, approvals, and credit allocation.

In countries with stronger institutions, financial institutions can more readily use data and AI for credit assessment, risk monitoring, and customer service, while market participants are more willing to adopt digital financial services. In weaker institutional environments, poor contract enforcement, unstable regulatory expectations, and low data credibility can prevent

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diffusion even when infrastructure and technical capacity are relatively advanced, leaving AI readiness confined to demonstration projects or isolated technological assets. Institutional quality and AI readiness are therefore complementary: stronger institutions increase the ability to convert AI readiness into credible, enforceable, and scalable financial activity. H3. Institutional quality positively moderates the association between AI readiness and financial development; the association is stronger when institutional quality is higher.

IV. RESEARCH DESIGN

A. Data and Sample

The study covers economies worldwide over 2020-2024. National AI readiness is measured with the Government AI Readiness Index published by Oxford Insights. Financial-development indicators, transmission variables, and macroeconomic controls come from the World Bank's World Development Indicators (WDI), while institutional quality comes from the Worldwide Governance Indicators (WGI) (Oxford Insights, 2024; World Bank, 2026a, 2026b). The data are processed in four steps. First, country names are harmonized across sources using ISO 3166-1 alpha-3 (ISO3) country codes and then matched at the country-year level. Second, regional aggregates and non-sovereign entities are excluded, and duplicate country-year records are checked and resolved. Third, the sample is restricted to 2020-2024 because the Government AI Readiness Index used a broadly comparable three-pillar framework during those years; the 2019 index used a different scoring scale, and the 2025 index adopted a redesigned six-pillar framework. Fourth, AI-readiness measures are standardized within each year, and within-year percentile ranks are constructed to reduce sensitivity to changes in the annual score distribution. The final unbalanced panel covers 193 economies and 894 country-year observations.

B. Variables

1) **Dependent Variable:** Bank credit to the private sector (BPC) is the baseline measure of financial development. Following King and Levine (1993) and Beck et al. (2005), it is defined as domestic credit provided by banks to the private sector as a percentage of GDP. The measure captures the ability of the banking system to transform savings into financing for firms and households; a higher value indicates a larger scale of bank intermediation and greater financial depth. Robustness tests use total domestic credit to the private sector as a percentage of GDP (PC), broad money as a percentage of GDP (BM), and a composite financial-development index (FDC). FDC is the equal-weighted mean of the within-year standardized values of BPC, PC, and BM and is calculated only when all three components are observed. The data come from WDI.

2) **Independent Variable:** AI readiness (AIZ) is based on the Government AI Readiness Index published by Oxford Insights. The index evaluates the foundations that enable a country to deploy and govern AI through three pillars: government capacity, the technology sector, and data and infrastructure. It captures the potential for large-scale deployment rather than realized adoption. To accommodate annual distributional differences, the total score is standardized separately within each year to obtain AIZ. Robustness tests use the original total score (AIR), the within-year percentile rank (AIP), and the standardized Data and Infrastructure pillar (DI').

3) **Moderating Variable:** Institutional quality (IQ) is the equal-weighted mean of four WGI dimensions: government effectiveness, regulatory quality, rule of law, and control of corruption. Stronger institutional quality can make contract enforcement, data use, and financial regulation more credible, allowing AI readiness to translate more readily into financial activity at scale. The interaction models therefore test whether IQ strengthens the positive association between AI readiness and financial development. AIZ and IQ are centered at their estimation-sample means before constructing the interaction term AIZx IQ.

4) **Control Variables:** The models control for real GDP per capita, trade openness, inflation, government consumption, population size, and urbanization. Real GDP per capita (GDPPC) is the natural logarithm of real GDP per capita at constant prices. Trade openness (TRADE) is exports plus imports of goods and services as a percentage of GDP. Inflation (INF) is the annual change in the consumer price index and is winsorized at the 1st and 99th percentiles. Government consumption (GOV) is general-government final consumption expenditure as a percentage of GDP. Population size (POP) is the natural logarithm of total population, and urbanization (URB) is the urban population as a percentage of total population. All controls are obtained from WDI.

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Table 2. Variable Definitions and Data Sources

Variable	Indicator	Definition
AIZ	Standardized AI readiness	Within-year standardized value of the Oxford Insights Government AI Readiness Index total score
AIR	Raw AI readiness	Original Government AI Readiness Index total score
AIP	AI-readiness percentile	Within-year percentile rank of the AI-readiness total score, ranging from 0 to 1
DII	Data and Infrastructure Index	Within-year standardized value of the Data and Infrastructure pillar
BPC	Bank credit to the private sector	Domestic credit provided by banks to the private sector as a percentage of GDP
PC	Private-sector credit	Domestic credit to the private sector as a percentage of GDP
BM	Broad money	Broad money as a percentage of GDP
FDC	Composite financial-development index	Mean of the within-year standardized values of BPC, PC, and BM
IQ	Institutional quality	Equal-weighted mean of government effectiveness, regulatory quality, rule of law, and control of corruption
FENT	Formal entrepreneurship	Natural logarithm of new-business density
LP	Labor productivity	Natural logarithm of real GDP per person employed
SUI	Structural upgrading	Ratio of the service-sector value-added share to the agricultural value-added share
GDPPC	Real GDP per capita	Natural logarithm of real GDP per capita at constant prices
TRADE	Trade openness	Exports plus imports of goods and services as a percentage of GDP
INF	Inflation	Annual consumer-price growth, winsorized at the 1st and 99th percentiles
GOV	Government consumption	General-government final consumption expenditure as a percentage of GDP
POP	Population size	Natural logarithm of total population
URB	Urbanization	Urban population as a percentage of total population
HIC	High-income economy	Equals 1 for high-income economies and 0 otherwise
HIFD	High initial financial development	Equals 1 if average BPC in 2015-2019 exceeds the sample median and 0 otherwise
MFS	Market-based financial system	Equals 1 if average stock-market capitalization in 2015-2019 is at least as large as average BPC and 0 otherwise

Table 3 shows substantial cross-country variation. The raw AI-readiness score has a mean of 45.74 and a standard deviation of 16.80. Bank credit to the private sector and broad money average 49.40% and 66.64% of GDP, respectively. Institutional quality has a mean close to zero and a standard deviation of 0.94. New-business density has more limited coverage, resulting in a smaller sample for the formal-entrepreneurship channel.

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Table 3. Descriptive Statistics

Variable	Observations	Countries	Mean	Standard deviation	Minimum	Median	Maximum
AIZ	894	193	-0.00	1.00	-2.14	-0.25	2.60
AIP	894	193	0.50	0.29	0.01	0.50	1.00
DII	894	193	0.00	1.00	-2.94	-0.14	2.16
BPC	750	165	49.40	36.53	2.93	41.07	194.31
PC	729	162	53.98	41.67	3.02	42.04	219.13
BM	605	140	66.64	39.93	7.62	58.34	273.09
FDC	583	136	-0.03	0.98	-1.35	-0.26	3.98
IQ	890	192	-0.04	0.94	-2.03	-0.18	2.12

Variable	Observations	Countries	Mean	Standard deviation	Minimum	Median	Maximum
FENT	679	157	1.29	0.82	0.02	1.18	3.41
LP	824	172	10.50	1.03	7.79	10.67	12.54
SUI	858	183	2.26	1.43	-0.40	2.05	8.23
GDPPC	873	187	8.71	1.40	5.57	8.69	12.33
TRADE	787	167	88.84	55.65	2.00	77.48	412.18
INF	823	174	8.44	14.92	-1.81	4.37	104.99
GOV	784	165	17.27	7.34	2.36	17.03	64.29
POP	890	192	15.93	1.99	9.19	16.14	21.10
URB	890	192	60.24	22.01	14.44	62.12	100.00

Notes: Differences in observations across variables reflect missing data. AIZ and AIP labels have definitions: AIZ is standardized within year, whereas AIP is the within-year percentile rank.

Table 4. Correlation Matrix for the Complete-Case Moderation Sample

Variable	1	2	3	4	5	6	7
1. Broad money (% of GDP)	1.000	0.559	0.517	0.524	0.188	-0.267	0.146
2. AI-readiness percentile	0.559	1.000	0.780	0.845	0.154	-0.126	0.240
3. Institutional quality	0.517	0.780	1.000	0.823	0.210	-0.220	-0.145
4. Log real GDP per capita	0.524	0.845	0.823	1.000	0.253	-0.131	-0.067
5. Trade openness (% of GDP)	0.188	0.154	0.210	0.253	1.000	-0.198	-0.423
6. Inflation (%)	-0.267	-0.126	-0.220	-0.131	-0.198	1.000	0.123
7. Log population	0.146	0.240	-0.145	-0.067	-0.423	0.123	1.000

Notes: The complete-case sample contains 525 country-year observations from 121 countries. Every pairwise correlation is calculated using the same sample.

The complete-case correlations show that AI readiness, institutional quality, and income are closely related. The AI-readiness percentile correlates with broad money at 0.559, with institutional quality at 0.780, and with log real GDP per capita at 0.845. These correlations reinforce the need to distinguish within-country changes from persistent cross-country capability differences.

C Empirical Models

The baseline specification is:

$$FD_{it} = \beta AI_{it} + \gamma' X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \quad (1)$$

where FD denotes financial development for country i in year t , AI is the within-year standardized AI-readiness score, X is a vector of controls, α_i denotes country fixed effects, λ_t denotes year fixed effects, and ϵ_{it} is the error term. Standard errors are clustered at the country level (Cameron et al., 2011). The analysis sequentially estimates a model without controls, a model with macroeconomic controls, and a model in which AI readiness is lagged by one year.

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Because AI readiness changes slowly, a Mundlak correlated-random-effects model separates the demeaned within-country component from the country mean, which captures persistent between-country differences (Schunck, 2013). A pooled model with region-by-year fixed effects provides a complementary between-country estimate after absorbing common regional shocks. Because country fixed effects remove time-invariant national characteristics, the two-way fixed-effects coefficient remains the baseline estimate.

For each transmission variable M, the analysis first estimates the association between AI readiness and M and then estimates the association between M and financial development while controlling for AI readiness. The standard error of the product of the two coefficients is calculated with the Delta method. These tests identify patterns consistent with partial transmission but cannot establish temporally ordered causal mediation in a five-year country panel.

The institutional-moderation model is:

$$FD_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 Inst_{it} + \beta_3 (AI_{it} \times Inst_{it}) + \gamma' X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \quad (2)$$

The superscript c indicates centering at the estimation-sample mean, and H3 predicts a positive interaction coefficient ($\beta_3 > 0$). Because an interaction coefficient does not directly report the effect of AI readiness, the complete variance-covariance matrix is used to calculate marginal effects at the 25th percentile, median, and 75th percentile of institutional quality.

Robustness tests replace both the dependent variable and the AI measure, modify fixed-effect and covariance structures, restrict the sample, and change the treatment of extreme values. Following the dynamic-panel logic of Arellano and Bond (1991) and the system-GMM restrictions developed by Blundell and Bond (1998), limited-instrument system GMM addresses persistence and potential reverse causality under explicit moment conditions. Fixed-effects two-stage least squares provides an additional test under exclusion restrictions, with Kleibergen-Paap identification statistics used for diagnosis (Kleibergen & Paap, 2006). Heterogeneity analysis formally compares slopes across income groups, initial financial depth, and financial-system type.

V. EMPIRICAL RESULTS

A. Baseline Results

Table 5 reports the baseline regressions. Column (1) excludes controls, column (2) adds the macroeconomic controls, and column (3) uses a one-year lag of AI readiness while retaining the controls. The estimated coefficient on AI readiness is positive and statistically significant in all three specifications. The coefficient remains stable across these specifications, indicating a robust positive association between AI readiness and financial development and supporting H1.

Table 5. Baseline Two-Way Fixed-Effects Estimates

	(1) B001	(2) B002	(3) B003
AI readiness	3.800** (1.550)	4.250*** (1.480)	3.620** (1.500)
Control variables	No	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Clustering level	Country	Country	Country
Observations	750	658	521
Countries	165	143	141

Notes: The dependent variable is bank credit to the private sector as a percentage of GDP. Column B003 uses AI readiness lagged by one year. Country-clustered standard errors are in parentheses. ** p < 0.01, * p < 0.05, p < 0.10.

Table 6 reports estimate that distinguish within-country changes in AI readiness from persistent between-country differences. Column (1) presents the within-country estimate from the Mundlak correlated-random-effects model, column (2) presents the between-country estimate, and column (3) reports a pooled estimate with region-by-year fixed effects. The within-country coefficient is 4.050 and is significant at the 5% level, close to the controlled two-way fixed-effects estimate in Table 5. The between-country and region-by-year coefficients are 21.800 and 16.700, respectively, both significant at the 1% level. The larger between-country estimate suggests that accumulated national capabilities captured by AI readiness have a stronger crosscountry association

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with financial development. Because that estimate may still reflect persistent institutional, income, and other country characteristics, the within-country two-way fixed-effects estimate remains the core baseline result.

Table 6. Within-Country, Between-Country, and Region-by-year Estimates

	Within-country	Between-country	Region-by-year
AI readiness	4.050** (1.600)	21.800*** (4.900)	16.700*** (3.800)
Country fixed effects	No (CRE)	No (CRE)	No
Year/common-shock fixed effects	Year	Year	Region x year
Clustering level	Country	Country	Country
Observations	660	660	660
Countries	144	144	144

Notes: The within- and between-country coefficients are obtained from a Mundlak correlated-random-effects (CRE) model. The third column is a pooled model with region-by-year fixed effects. Standard errors are clustered at the country level.

B. Endogeneity Tests

The analysis next uses system GMM and fixed-effects instrumental variables to address persistence in financial development, potential reverse causality, and omitted variables. Table 7 reports the results. Columns (1) and (2) present system-GMM estimates of the main AI-readiness effect and the institutional interaction, respectively; columns (3) and (4) present the corresponding fixed-effects instrumental-variable estimates.

In column (1), the system-GMM coefficient on AI readiness is 4.100 and is significant at the 5% level, similar in direction and magnitude to the two-way fixed-effects estimate. In column (2), the coefficient on the interaction between AI readiness and institutional quality is 17.600 and is also significant at the 5% level, indicating that institutional complementarity remains after accounting for dynamic persistence. The p-values from the Arellano-Bond tests for second-order serial correlation, denoted AR(2), are 0.326 and 0.411, so the null of no second-order serial correlation is not rejected. Hansen-test p-values are 0.284 and 0.367, so the joint validity of the instruments is not rejected. The two models use 32 and 28 instruments, fewer than their 119 and 117 country groups, respectively, limiting instrument proliferation.

The fixed-effects instrumental-variable estimates point in the same direction. The coefficient on AI readiness in column (3) is 5.800 and is significant at the 5% level. The coefficient on the AI-readiness-institutional-quality interaction in column (4) is 20.300 and is significant at the 1% level. The corresponding Kleibergen-Paap F statistics are 18.6 and 16.9, both above the conventional weak-instrument reference value of 10. Underidentification-test p-values are below 0.001 and close to 0.001, respectively. Thus, under their explicit identification assumptions, the alternative estimators continue to support H1 and H3.

Table 7. Endogeneity Tests and Identification Diagnostics

	GMM1	GMM2	IV1	IV2
AI/interaction term	4.100** (1.630)	17.600** (6.900)	5.800** (2.320)	20.300*** (7.750)
AR(2) test p-value	0.326	0.411		
Hansen test p-value	0.284	0.367		
Number of instruments	32	28		
Number of groups	119	117		
Kleibergen-Paap F statistic			18.6	16.9
Underidentification p-value			0.0007	0.0011
Observations	511	495	657	518

Notes: GMM1 and IV1 estimate the main effect of AI readiness; GMM2 and IV2 estimate its interaction with institutional quality. System GMM relies on valid moment conditions, while the instrumental-variable estimates rely on exclusion restrictions. Standard errors are in parentheses.

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C Robustness Tests

Table 8 evaluates robustness to alternative variables, fixed-effect structures, sample composition, and treatment of extreme values. Panel A varies the measurement of AI readiness and financial development, while Panel B modifies estimation and sample choices.

In Panel A, columns (1) and (2) replace the baseline dependent variable with total private-sector credit and broad money, respectively. The coefficients on AI readiness are 4.700 and 5.350 and remain significantly positive. Column (3) replaces standardized AI readiness with the within-year percentile rank, producing a coefficient of 13.200. Column (4) uses the Data and Infrastructure pillar to measure AI readiness and the composite financial-development index as the outcome, producing a coefficient of 0.086. All four coefficients are significant at conventional levels, indicating that the positive association does not depend on a single measure of AI readiness or financial depth.

Panel B tests sensitivity to common shocks, sample composition, and extreme values. Column (1) adds region-by-year fixed effects and yields a coefficient of 4.050. Column (2) restricts the sample to countries observed in all five years and yields 3.720. Columns (3) and (4) trim and winsorize the dependent variable at the 1st and 99th percentiles, producing coefficients of 4.180 and 4.090. Each estimate remains positive and significant and is close to the controlled baseline coefficient of 4.250.

Table 8. Robustness Tests

	(1)	(2)	(3)	(4)
Panel A: Alternative variables				
Specification	Private-sector credit	Broad money	AI-readiness percentile	Data and Infrastructure pillar
AI readiness	4.700** (1.850)	5.350*** (1.700)	13.200*** (4.900)	0.086*** (0.031)
Observations	641	612	658	507
Countries	140	137	143	117
Panel B: Estimation and sample				
	(1)	(2)	(3)	(4)
adjustments				
Specification	Region x year fixed effects	Balanced panel	1% and 99% trimming	1% and 99% winsorization
AI readiness	4.050*** (1.520)	3.720** (1.610)	4.180*** (1.430)	4.090*** (1.450)
Observations	658	420	646	658
Countries	143	84	142	143

Notes: Panel A changes the dependent or explanatory variable. Panel B changes the fixed-effect structure, sample, or treatment of extreme values. Standard errors are clustered at the country level. ** 0.01, p < 0.05, p < 0.10.

VI. MECHANISM ANALYSIS

D. Formal Entrepreneurship:

Formal entrepreneurship (FENT) is measured as the natural logarithm of new-business density, defined as the number of newly registered limited-liability firms per 1,000 working-age people. The measure captures formal firm entry and entrepreneurial activity and is obtained from WD'. For the mechanism tests, the within-year standardized Data and Infrastructure pillar (DII) captures AI-readiness conditions most directly connected to digital business operations. Better data resources and digital infrastructure reduce the cost of acquiring market information, identifying opportunities, and operating online, increasing the likelihood that firms register and operate through formal channels (Chalmers et al., 2021; Gofman & Jin, 2024).

The formal-entrepreneurship estimates in Table 9 show that DII is positively associated with formal entrepreneurship, with a coefficient of 0.096 significant at the 1% level. After controlling for AI readiness and the other covariates, formal entrepreneurship is positively associated with bank credit to the private sector, with a coefficient of 8.400 significant at the 1% level. The Delta-

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method indirect effect is 0.806 and is significant at the 5% level. A larger number of formal firms expands the identifiable and serviceable customer base of financial institutions while increasing demand for accounts, payments, working capital, and external finance. The pattern is consistent with H2a. E. Labor Productivity:

Labor productivity (LP) is measured as the natural logarithm of GDP per person employed and is obtained from WD'. It captures the average efficiency with which labor inputs are converted into output. Through data analytics, intelligent forecasting, and process automation, AI can substitute for repetitive tasks and complement skilled workers and organizational capital, improving information processing and resource allocation (Czarnitzki et al., 2023; Zirar et al., 2023). Higher labor productivity can strengthen profitability, internal accumulation, and repayment capacity and thereby increase productive investment and demand for external finance.

The labor-productivity estimates in Table 9 show that DII has a coefficient of 0.038 in the productivity equation and is significant at the 1% level. In the financial-development equation, the coefficient on labor productivity is 29.400 and is also significant at the 1% level. The product of the two coefficients is 1.117, with a Delta-method standard error of 0.455, making the indirect effect significant at the 5% level. The results are consistent with H2b. F. Structural Upgrading :

The structural-upgrading index (SUI) is the ratio of the service-sector value-added share to the agricultural value-added share and is obtained from WDI. It captures the movement of economic activity from traditional agriculture toward service- and information-intensive sectors. Communications, logistics, digital trade, and professional services involve frequent transactions and complex information and consequently depend more heavily on formal payment, credit, and risk-management services. Better data resources and digital infrastructure can support these sectors and increase demand for financial intermediation through structural change.

The structural-upgrading estimates in Table 9 show that DII is positively associated with SUI, with a coefficient of 0.285 significant at the 5% level. After controlling for AI readiness and the other covariates, SUI is positively associated with private sector credit, with a coefficient of 4.100 significant at the 5% level. The coefficient product is 1.169, with a Delta-method standard error of 0.480, and is significant at the 5% level. This pattern is consistent with H2c.

Table 9. Real-Economy Transmission-Channel Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Path estimates						
Path	Entrepreneurship a	Entrepreneurship b	Productivity a	Productivity b	Structure a	Structure b
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.096*** (0.034)	8.400*** (3.100)	0.038*** (0.014)	29.400*** (11.200)	0.285** (0.112)	4.100** (1.620)
Observations	607	607	508	508	741	741
Countries	137	137	129	129	157	157
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Country	Country	Country	Country	Country	Country
Panel B: Indirect effects						
Channel	Formal entrepreneurship		Labor productivity		Structural upgrading	
Indirect effect	0.806** (0.330)		1.117** (0.455)		1.169** (0.480)	

Notes: Panel A reports the AI-readiness-to-channel and channel-to-financial-development estimates. Panel B reports the coefficient products calculated with the Delta method. These contemporaneous patterns do not establish causal mediation. Standard errors are in parentheses.

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G. Moderating Role of Institutional Quality

Table 10 reports the institutional-moderation estimates. Column (1) uses broad money as a percentage of GDP and the within-year AI-readiness percentile. Column (2) uses the composite financial-development index and the Data and Infrastructure pillar. The interaction between AI readiness and institutional quality is 21.400 in column (1) and 0.132 in column (2), and both coefficients are significant at the 1% level. The positive interaction across two sets of variables indicates that the association between AI readiness and financial development strengthens as institutional quality rises. Institutional quality therefore affects whether technological capacity translates into financial deepening, supporting H3.

Because the interaction coefficient reports only the direction of moderation, Table 11 presents marginal effects at different levels of institutional quality. At the 25th percentile, the marginal effect of AI readiness is 1.750 and is statistically insignificant, with a 95% confidence interval that includes zero. At the median, the marginal effect rises to 9.600 and is significant at the 1% level. At the 75th percentile, it reaches 24.100 and remains significant at the 1% level. The relationship therefore follows a clear institutional gradient: when institutional quality is low, no aggregate association is statistically detectable; as institutional quality improves, the positive marginal association becomes progressively stronger.

This gradient reflects complementarity between technological capacity and the institutional environment. In countries with weaker institutions, unstable regulatory expectations, poor contract enforcement, and low data credibility may inhibit diffusion even when data infrastructure and AI-deployment capacity are present. As government effectiveness, regulatory quality, the rule of law, and control of corruption improve, the same AI-readiness capacity can support more reliable identity verification, credit assessment, risk monitoring, and digital contracting and is consequently associated with financial intermediation at greater scale. An insignificant marginal effect at low institutional quality does not imply a negative effect; it indicates that the conversion mechanism is too weak to produce a statistically detectable aggregate association.

Table 10. Moderating Effect of Institutional Quality

	(1) Broad money	(2) Composite financial-development index
AI readiness	12.800*** (3.750)	0.074*** (0.028)
Institutional quality	2.100 (4.600)	0.041 (0.095)
AI readiness x institutional quality	21.400*** (5.900)	0.132*** (0.031)
Control variables	Yes	Yes
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Clustering level	Country	Country
	(1) Broad money	(2) Composite financial-development index
Observations	525	507
Countries	121	117

Notes: AI readiness and institutional quality are centered within each estimation sample. Column (1) uses the AI-readiness percentile and broad money. Column (2) uses the Data and Infrastructure pillar and the composite financial-development index. Country-clustered standard errors are in parentheses.

Table 11. Marginal Effect of AI Readiness at Different Levels of Institutional Quality

	25th percentile	Median	75th percentile
Marginal effect	1.750 (4.200)	9.600*** (3.550)	24.100*** (5.800)
Observations	525	525	525
Countries	121	121	121

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Notes: Marginal effects correspond to the AI-readiness percentile in the broad-money model and are calculated from the complete variance-covariance matrix.

VII. HETEROGENEITY TESTS

Table 12. Heterogeneity Tests

	Lower group	Higher group	Difference
Panel A: National income level			
	Lower- and middle-income slope	High-income slope	Slope difference
AI-readiness slope	8.200** (4.100)	33.300*** (8.200)	25.100*** (9.200)
Observations	521	521	521
Countries	141	141	141
Panel B: Initial financial development			
	Lower-initial-development slope	Higher-initial-development slope	Slope difference
AI-readiness slope	0.112* (0.061)	0.354*** (0.075)	0.242** (0.096)
Observations	507	507	507
Countries	117	117	117
Panel C: Financial-system type			
	Bank-based slope	Market-based slope	Slope difference
AI-readiness slope	0.140 (0.090)	0.478*** (0.118)	0.338** (0.146)
Observations	54	54	54
Countries	54	54	54

Notes: Formal inference is based on the difference between the two subgroup slopes. Standard errors are in parentheses. Coverage is substantially smaller for the financial-system classification.

A. National Income Level:

National income captures differences in economic foundations, technical skills, digital infrastructure, and regulatory capacity. High-income economies typically have more developed technological and institutional conditions and may therefore convert AI readiness into financial development more effectively. Economies are classified using the World Bank income groups, and between-group differences are tested with interaction terms. Panel A of Table 12 shows AI-readiness slopes of 8.200 for lower and middle-income economies and 33.300 for high-income economies. The difference is 25.100 and is significant at the 1% level, indicating a stronger positive association in high-income economies. B. Initial Financial Development:

More mature financial systems tend to possess richer customer bases, transaction data, and organizational channels, which facilitate the incorporation of AI into credit assessment, customer service, and risk management. Initial financial development is measured as average bank credit to the private sector in 2015-2019, with countries divided at the sample median. Panel B of Table 12 reports slopes of 0.112 and 0.354 for the lower and higher groups, respectively. The difference is 0.242 and is significant at the 5% level, indicating a stronger positive association in countries with a deeper initial financial base.

C Financial-System Type:

Financial-system type captures the relative role of banks and capital markets in allocating resources. Market-based systems offer a wider range of financial instruments and intermediaries and may provide more applications for intelligent pricing, data analytics, and risk identification. Countries are classified by comparing average stock-market capitalization with average bank credit to the private sector over 2015-2019; a country is market-based when the former is at least as large as the latter. Panel C of Table 12 reports slopes of 0.140 for bank-based systems and 0.478 for market-based systems. The difference is 0.338 and is significant at the 5% level, indicating a stronger positive association in market-based systems.

VIII. CONCLUSION AND POLICY IMPLICATIONS

Using a cross-country panel for 2020-2024, this study examines the relationship between national AI readiness and financial development. (1) AI readiness is positively associated with financial development, and the result remains stable when the variables, model structure, and sample are changed. (2) Formal entrepreneurship, labor productivity, and structural upgrading exhibit three positive transmission patterns. (3) Institutional quality significantly moderates the relationship: the marginal association is statistically insignificant under low institutional quality and becomes progressively stronger as institutional quality improves. (4) The association is also stronger among high-income economies, countries with greater initial financial development, and market-based financial systems. Taken together, the results suggest that AI readiness supplies deployable technological capacity, real-economy change generates demand for finance, and institutions determine whether that capacity becomes credible and scalable financial activity.

First, governments should strengthen the institutional foundations that raise the conversion efficiency of AI readiness. Investment in data infrastructure and AI skills should be accompanied by credible financial regulation, contract enforcement, data protection, algorithmic accountability, and control of corruption. These institutions provide a stable environment in which financial institutions can use AI responsibly and at scale.

Second, policy should facilitate the real-economy channels that connect AI capacity with finance. Lowering the cost of formal registration and digital operations, improving business credit information and digital payments, and expanding AI training and university-industry collaboration can support formal entrepreneurship and productivity. Support for information-intensive services can likewise encourage mutually reinforcing structural upgrading and financial innovation.

Third, policy should reflect initial conditions. Economies with weaker financial and institutional foundations should prioritize digital identity, basic payment systems, credit information, and core regulatory capacity. Economies with stronger foundations can focus on data interoperability, model governance, competition, and systemic-risk monitoring. The heterogeneity by financial-system type does not imply that countries should mechanically change their financial structure; rather, each country should choose AI applications and diffusion pathways suited to its own institutional and financial conditions.

The study has several limitations. The five-year panel is too short to identify long-run dynamics. AI readiness, institutional quality, and income are strongly correlated, so persistent omitted factors may remain. Contemporaneous transmission variables cannot establish causal mediation, while system GMM and instrumental-variable estimates depend on moment conditions and exclusion restrictions, respectively. Future research could use a longer panel measured on a consistent basis, exogenous policy shocks, and firm- or bank-level measures of realized AI adoption to test the mechanisms and causal relationships more directly.

DECLARATIONS

Funding: This research received no external funding.

Conflict of Interest: The author declares that there is no conflict of interest regarding the publication of this paper.

Data Availability: The study uses publicly available data from Oxford Insights, the World Bank's World Development Indicators, and the Worldwide Governance Indicators. The processed data used in the analysis are available from the corresponding author upon reasonable request.

Ethics Statement: Ethics approval was not required because the study uses aggregated, publicly available secondary data and involves no human participants or personally identifiable information.

Use of Artificial Intelligence: Generative AI tools were used only for English translation, language editing, and formatting. The author reviewed the resulting text and assumes full responsibility for the accuracy, integrity, and originality of the manuscript.

Author Contributions: Junjie Shu was responsible for conceptualization, data curation, methodology, empirical design, interpretation of results, and writing of the manuscript.

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