

Digital adoption as a compensatory mechanism for resource scarcity: Entrepreneurial Leadership, Sustainable Innovation and National AI Capacity in Emerging Economies

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ABSTRACT

Research on entrepreneurial leadership, digital transformation and sustainable innovation remains fragmented, confined largely to single-country samples and cross-sectional in design. Few studies observe all three in the same entrepreneurs, compare emerging with advanced economies or consider how intensively countries actually use artificial intelligence (AI). This study asks whether digital transformation links leadership to sustainable innovation and growth, and whether national AI capacity amplifies that link or whether digital tools instead substitute for resource scarcity. Drawing on institutional-voids theory, we analyse Global Entrepreneurship Monitor data on 86,176 entrepreneurs in 58 economies (2021–2022), linked to national measures of AI preparedness, revealed generative-AI use and developer density. Leadership is modelled as a latent construct and tested for measurement invariance; associations are estimated with country $\times$ year fixed effects, a multi-group structural equation model and doubly robust estimators, complemented by a difference-in-differences analysis of the release of ChatGPT. Entrepreneurial leadership is associated with digital adoption, product innovation and growth expectations, including among entrepreneurs who lead employees or co-owners. Digital adoption is associated with 7–14 percentage points more in environmental, social and innovative activity, and these associations survive omitted-variable bounds, timing checks and common-method tests. The link between digital adoption and environmental action is about 2.5 times stronger in emerging economies and weakens as national AI capacity rises, whereas national AI capacity does not amplify leadership, and the release of ChatGPT left no detectable mark on national business entry. The results support a substitution rather than an amplification view of the AI era: digital tools contribute most to sustainable entrepreneurship where institutional and technological capabilities are scarcest.

Keywords: Entrepreneurial leadership; Digital transformation; Sustainable innovation; Artificial intelligence; Institutional voids; Emerging economies; Global Entrepreneurship Monitor.

Introduction

Generative artificial intelligence (AI) is spreading rapidly through the economy and already raises the productivity of knowledge work (Noy & Zhang, 2023; Brynjolfsson et al., 2025). Its reach is broad, large language models are relevant to most occupations (Eloundou et al., 2024) but the capacity to benefit from it is not: advanced economies are far better prepared than emerging and low-income ones (Cazzaniga et al., 2024). For entrepreneurs, AI can augment or replace tasks in idea generation, selling and scaling (Chalmers et al., 2021; Obschonka & Audretsch, 2020), and early quasi-experimental evidence from China links the release of ChatGPT to a surge in small-firm formation (Cai et al., 2025). These developments coincide with a second shift, the convergence of the digital and green transitions into a single “twin transition” in which digital technologies support eco-innovation (Montresor & Vezzani, 2023; Menéndez & Lavopa, 2025).

Entrepreneurial leadership (EL), the capacity to recognise and exploit opportunities while mobilising others towards innovative goals sits at the centre of both transitions and has been linked to digital transformation in firm-level studies (Wu et al., 2021; Schiuma et al., 2022). Yet the evidence base has three limitations. First, it is fragmented and confined largely to single-country samples, and the multidimensional structure of EL is rarely tested at scale (Hoang et al., 2025; Bagheri & Harrison, 2020). Second, few studies observe leadership, digital transformation, sustainable innovation and growth in the same entrepreneurs across different institutional settings, although entrepreneurial orientation is inherently multilevel (Wales et al., 2020). Third, national AI capacity is usually captured by readiness indices alone, so it remains unclear whether AI-intensive environments strengthen the returns to individual capabilities or whether digital tools matter most where such capabilities are scarce.

This study addresses three research questions. RQ1 asks whether EL, measured consistently across countries, is associated with digital transformation, sustainable innovation and growth expectations. RQ2 asks whether digital transformation links leadership to sustainable innovation and whether this link differs between emerging and advanced economies. RQ3 asks whether national AI capacity readiness, revealed use and developer talent amplifies these relationships, and whether the generative-AI shock altered national business entry. Emerging economies are a critical setting because they combine high entrepreneurial activity with institutional voids and the lowest levels of AI adoption (Soluk et al., 2021; Appel et al., 2025).

To answer these questions, we pair Global Entrepreneurship Monitor (GEM) survey data, which observe leadership, digital adoption, sustainable action and growth expectations for the same entrepreneurs, with three national measures that capture distinct facets of AI capacity (Section 4). The study makes three contributions. First, it shows that GEM's entrepreneurial-cognition items measure a coherent latent leadership construct once a wording artefact is modelled, and that the construct's associations hold among entrepreneurs who lead employees or co-owners. Second, it identifies digital transformation as the main channel through which leadership reaches sustainable innovation and growth. Third, by testing amplification against substitution, it shows that this channel is strongest where economies are emerging and national AI capacity is low a pattern that, to our knowledge, has not been examined with revealed AI-use data (Handa et al., 2025; Appel et al., 2025).

Literature Survey

A. Entrepreneurial leadership

EL has developed from a loose combination of leadership and entrepreneurship ideas into a distinct construct centred on influencing others to recognise and exploit opportunities. Scale-development work across two cultural contexts shows that it is multidimensional, combining entrepreneurial competencies with leadership behaviours and roles (Bagheri & Harrison, 2020). A systematic review of 93 empirical studies nevertheless concludes that the literature remains fragmented and lacks an integrative account of the construct's antecedents, consequences and boundary conditions (Hoang et al., 2025). Because entrepreneurial orientation operates at and across individual, firm and national levels (Wales et al., 2020), and national culture shapes how entrepreneurial self-efficacy translates into action (Schmutzler et al., 2019), cross-national designs are needed. At firm level, EL has been linked to digital transformation through ambidextrous learning (Wu et al., 2021), and reviews identify the leadership competencies that digital transformation requires (Schiuma et al., 2022). How EL relates to sustainability and growth across many countries, however, remains largely unexamined.

B. Digital transformation and the twin transition

Digital technologies have changed both the outcomes and the process of entrepreneurship, making it less bounded and more distributed (Nambisan et al., 2019). Digital transformation improves SME performance (Teng et al., 2022) and opens routes to sustainable entrepreneurship, because digital tools help

organisations address environmental and social challenges (George et al., 2021; Holzmann & Gregori, 2023). The twin-transition literature finds that digital and green technologies are complements: digital adopters eco-innovate more among Italian firms (Montresor & Vezzani, 2023), regions combine green and digital innovation (Faggian et al., 2025), and industrial firms in developing countries adopt the two jointly (Menéndez & Lavopa, 2025). Sustainable entrepreneurship has also become measurable at scale: researchers proposed extending GEM to cover it (Roomi et al., 2021), and GEM now reports entrepreneurs' environmental and social decisions (Hill et al., 2025). Growth aspirations, in turn, rise with product innovation, process innovation and internationalisation (Estrin et al., 2022) and are shaped by historical and institutional context (Decker et al., 2020).

C. Artificial intelligence and entrepreneurship

Research on AI and entrepreneurship has moved from agenda-setting to evidence. Early work argued that AI and big data open a new era for entrepreneurship (Obschonka & Audretsch, 2020) and that AI augments and replaces tasks in idea production, selling and scaling, with risks for traditional small firms (Chalmers et al., 2021). Case evidence shows AI reshaping successive phases of venture creation (Schiavone et al., 2023), reviews document AI as an enabler for entrepreneurs (Giuggioli & Pellegrini, 2023), and recent work examines generative AI in entrepreneurial education and practice (Dwivedi, 2025); AI is also changing how entrepreneurship is studied (Lévesque et al., 2022). Because generative AI raises productivity most for less experienced workers (Noy & Zhang, 2023; Brynjolfsson et al., 2025), it could narrow capability gaps between entrepreneurs. Whether it does so across countries depends on access: revealed usage is concentrated in high-income economies (Appel et al., 2025), and occupational exposure is broad but uneven (Eloundou et al., 2024; Handa et al., 2025).

D. Institutional voids and entrepreneurship in emerging economies

Emerging economies are characterised by institutional voids: missing or weak market-supporting institutions such as reliable intermediaries, information systems and contract enforcement. Entrepreneurs respond by substituting other resources for these institutions. They draw on political and family ties (Ge et al., 2019) and, increasingly, on digital technologies, which partly fill voids by supplying information, market access and coordination (Soluk et al., 2021; Hecks et al., 2021). Consistent with this view, digital adoption reshapes labour markets in developing countries (Finkelstein Shapiro & Mandelman, 2021), digital business transformation supports frugal innovation and SME resilience in emerging markets (Al Omoush et al., 2025), and cost-efficient green product innovation is attainable for SMEs in emerging economies (Maulidi, 2025). At the same time, organisational and national AI readiness are lowest precisely where institutional voids are deepest (Issa et al., 2022; Cazzaniga et al., 2024).

E. Research gaps

Table 1 synthesises representative studies and reveals four gaps. EL is rarely validated in large cross-national samples (*measurement*); leadership, digital transformation, sustainable innovation and growth are seldom observed together (*integration*); national AI capacity is proxied by readiness indices, and revealed AI use is absent from entrepreneurship research (*AI context*); and most evidence comes from single countries, which prevents systematic comparison of emerging and advanced economies (*institutional context*). The remainder of the paper addresses each gap in turn.

Table 1. Synthesis of representative prior studies and the gaps addressed.

Study	Context / data	Key finding	Gap addressed here
Bagheri & Harrison (2020)	Scale development; Iran and Scotland	EL is a multidimensional construct	Not validated in large cross-national samples
Hoang et al. (2025)	Systematic review of 93 empirical studies	EL literature remains fragmented	Calls for integrative, multi-context evidence
Wu et al. (2021)	Firm survey	EL enables digital transformation via ambidextrous learning	Single context; no sustainability or AI measures
Montresor & Vezzani (2023)	Italian firms	Digital technologies complement eco-innovation	Firms, not entrepreneurs; one country
Menéndez & Lavopa (2025)	Industrial firms, developing countries	Digital and green technologies adopted jointly	No leadership or growth outcomes
Soluk et al. (2021)	Developing countries	Institutional voids shape digital entrepreneurship	No sustainability or leadership outcomes
Estrin et al. (2022)	Individuals, 74 countries, 2001–2015	Innovation and internationalisation raise growth aspirations	No digital, sustainability or AI dimension
Al Omoush et al. (2025)	214 SME owners, emerging markets	Digital transformation supports frugal innovation and resilience	No comparison with advanced economies
Brynjolfsson et al. (2025)	Field data, customer support	Generative AI raises productivity, most for novices	Workers, not entrepreneurs
Cai et al. (2025)	Chinese firm registrations (grids)	ChatGPT followed by more small-firm entry	Single country; no cross-national test
Appel et al. (2025)	Claude usage, 150+ countries	AI use concentrated in high-income economies	Not linked to entrepreneurship outcomes

Theoretical Framework and Hypothesis

A. Entrepreneurial leadership and digital transformation

EL combines opportunity recognition, innovativeness, proactiveness, risk-taking and self-efficacy with the vision needed to mobilise resources (Bagheri & Harrison, 2020). Digital transformation draws on exactly these capabilities: leaders must identify digitally enabled opportunities, accept the uncertainty of new technologies and reorganise routines (Schiuma et al., 2022), and EL fosters the learning that such change requires (Wu et al., 2021). Because self-efficacy translates into entrepreneurial action across national contexts (Schmutzler et al., 2019), entrepreneurs who perceive opportunities and feel competent to exploit them should adopt digital technologies more readily.

H1. Entrepreneurial leadership is positively associated with digital transformation.

B. Digital transformation, sustainable innovation and growth

Digital technologies lower the cost of monitoring resource use, reaching customers and experimenting with new products, and they allow social and environmental objectives to be built into business models (George et al., 2021; Holzmann & Gregori, 2023). Firm-level evidence on the twin transition shows that digital adoption complements eco-innovation (Montresor & Vezzani, 2023; Menéndez & Lavopa, 2025), and AI increasingly supports organisational sustainability (Kulkov et al., 2024). Innovation, in turn, raises growth aspirations (Estrin et al., 2022). Leadership should therefore relate to sustainable innovation and growth both directly and through digital transformation.

H2. Digital transformation is positively associated with (a) environmental and social action and (b) product and process innovation.

H3. Entrepreneurial leadership, digital transformation and sustainable innovation are positively associated with growth expectations, and digital transformation transmits part of the association between leadership and these outcomes.

C. National AI capacity: amplification or substitution?

Institutional context may shape these relationships in two opposing ways. An *amplification* argument holds that AI preparedness, digital infrastructure and developer ecosystems lower the cost of AI and digital tools and thereby raise the returns to individual capabilities (Cazzaniga et al., 2024; Wachs et al., 2022). Leadership, on this view, should matter more where national AI capacity is high.

H4 (amplification). National AI capacity strengthens the associations of entrepreneurial leadership with digital transformation and growth expectations.

Institutional-voids theory implies the opposite. Where market-supporting institutions and complementary capabilities are scarce, digital tools substitute for them by supplying information, market access and coordination that entrepreneurs cannot otherwise obtain (Soluk et al., 2021; Heeks et al., 2021). The marginal contribution of digital adoption to sustainable innovation should therefore be largest in emerging economies, whereas leadership capabilities which depend on complementary institutions to be converted into innovation should yield less there (Ge et al., 2019; Al Omoush et al., 2025).

H5 (substitution). In emerging economies, digital transformation is more strongly, and entrepreneurial leadership less strongly, associated with sustainable innovation.

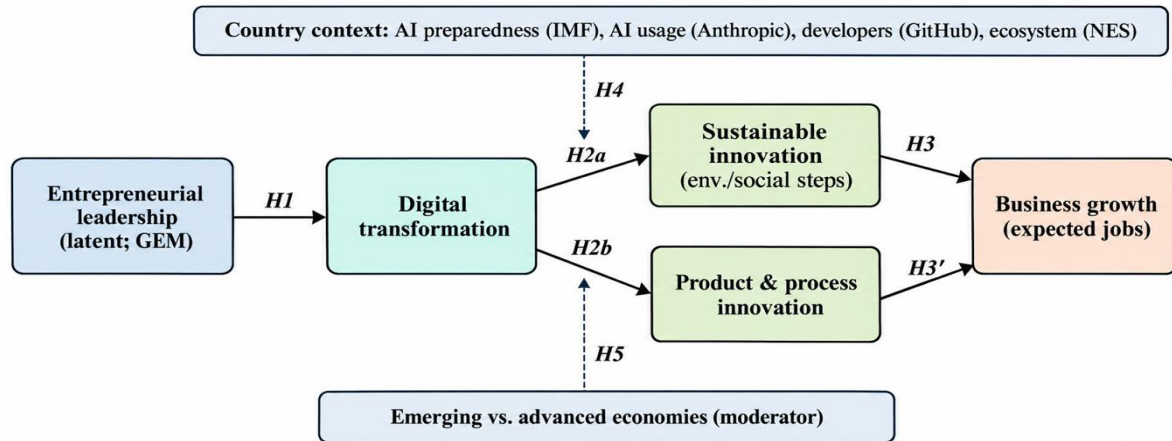


Figure 1. Conceptual framework and hypotheses.

Data and Methods

A. Research design and data

The design links three levels of data, each chosen for a specific test (Figure 2; Table 2). At the entrepreneur level we use the 2021–2022 waves of the GEM Adult Population Survey (Global Entrepreneurship Monitor, 2024), the only harmonised cross-national survey that asks the same respondents about entrepreneurial cognitions, digital technology use, environmental and social decisions, innovation and growth expectations (Hill et al., 2025). These waves cover 86,176 nascent entrepreneurs and owner-managers in 58 economies, 20 of them emerging (World Bank low- and middle-income economies at the time of retrieval). Fifteen economies did not field GEM's three mindset items, so the leadership analyses cover 43 economies (17 emerging) and the regression samples 41 economies after listwise deletion.

At the national level, H4 requires measures of AI capacity that capture different facets of it. We use the IMF AI Preparedness Index for institutional and infrastructural readiness (Cazzaniga et al., 2024), the Anthropic Economic Index for revealed generative-AI use per working-age person (Handa et al., 2025; Appel et al., 2025) and GitHub developer density for the talent base on which digital ventures draw (GitHub, 2025; Wachs et al., 2022). To test whether generative AI changed business entry (RQ3), we use World Bank new-business density for 2015–2024 (World Bank, 2025), with pre-ChatGPT digital intensity as the treatment intensity. Oxford Government AI Readiness (Oxford Insights, 2025), OECD environmental patents (OECD, 2025) and GEM National Expert Survey conditions (Rietveld & Patel, 2023) serve only to describe the national context (Section 5.8).

Table 2. Data sources and their role in the analysis.

Source	Level	Coverage used	Measures	Role
GEM Adult Population Survey	Entrepreneur	86,176 entrepreneurs; 58 economies; 2021–2022	Leadership items, digital adoption, sustainability, innovation, growth	H1–H3, H5
IMF AI Preparedness Index	Economy	173 economies; 2023	Institutional and infrastructural AI readiness	H4
Anthropic Economic Index	Economy	193 economies; Aug 2025–May 2026	Revealed generative-AI use per working-age person	H4; Fig. 3
GitHub Innovation Graph	Economy-year	213 economies; 2020–2025	Developer density	H4; RQ3
World Bank Entrepreneurship Database	Economy-year	117 economies; 2015–2024	New-business density	RQ3
World Development Indicators	Economy-year	2015–2024	Internet use, ICT service exports, GDP, population	RQ3; controls
Oxford AI Readiness; OECD patents; GEM NES	Economy	2021–2025	Government AI readiness, green patent share, framework conditions	Context (Fig. 9)

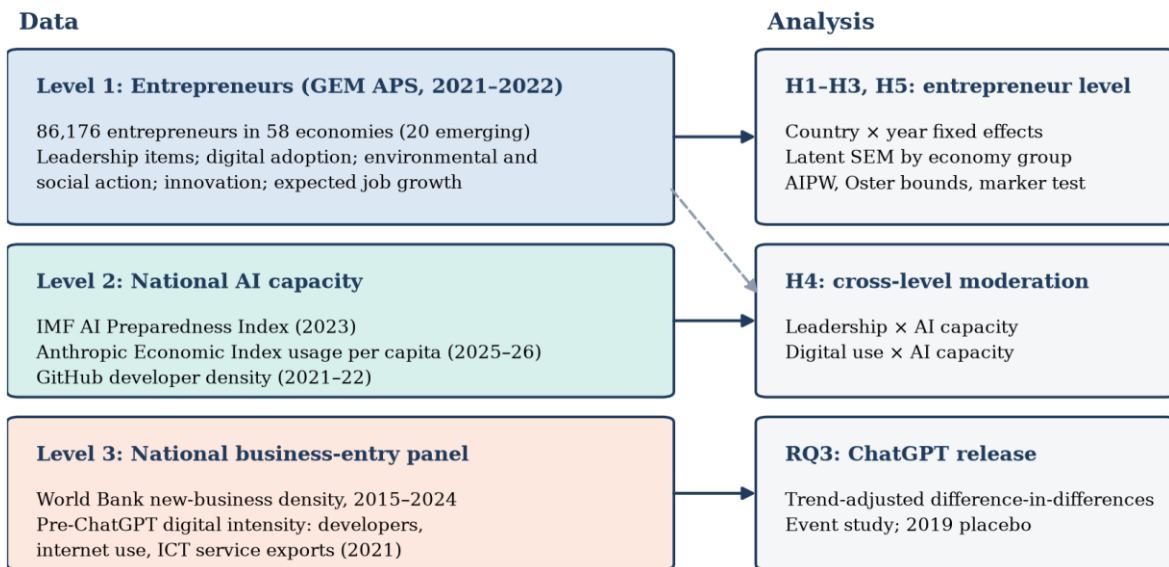


Figure 2. Research design: data levels and the analyses they inform.

B. Measures

Entrepreneurial leadership. Following the dimensions identified in measurement research (Bagheri & Harrison, 2020), we use six GEM items: opportunity recognition, opportunity alertness, proactiveness, innovativeness, self-efficacy and risk-taking (fear of failure, reversed). Three of the items are negatively worded, and some respondents answer such items inconsistently, which can produce a spurious method factor (Kam & Fan, 2020). We therefore model a latent leadership factor alongside an orthogonal wording factor (model M3 in Table 4) and use its standardised factor scores (EL). The motive “to make a difference in the world” captures leadership *vision* and enters the models separately.

Digital transformation is measured by whether the business uses digital technologies to sell (DT) and whether it adopted or enhanced them in response to the COVID-19 pandemic; *digital intention* is the expectation of using more digital technologies. *Sustainable innovation* is captured by steps taken in the past year to minimise environmental impact or to maximise social impact, and by new products and processes. *Growth expectation* is the log difference between expected employment in five years and current employment, following the growth-aspiration literature (Estrin et al., 2022). National moderators are standardised.

C. Estimation strategy

The baseline models are linear probability models (OLS for growth) with country × year fixed effects, which absorb all national shocks, and controls for age, age², gender, education, business stage and sector technology intensity; standard errors are clustered by country. Differences between emerging and advanced economies are estimated as interactions on the full sample rather than in split samples, which would rest on few countries. For entrepreneur i in country c and year t we estimate Equation (1), where E_c indicates an emerging economy, X the controls and μ_{ct} the country × year effects; β_2 and γ_2 test H5, and H4 is tested by replacing E_c with standardised measures of national AI capacity.

$$Y_{ict} = \beta_1 EL_{ict} + \beta_2 (EL_{ict} \times E_c) + \gamma_1 DT_{ict} + \gamma_2 (DT_{ict} \times E_c) + X'_{ict} \delta + \mu_{ct} + \varepsilon_{ict} \quad (1)$$

A latent structural equation model (SEM), fitted to country-year-demeaned data for all economies and separately for each economy group, estimates the direct and indirect paths jointly. Measurement invariance across economy groups is assessed with multi-group confirmatory factor analysis (Leitgöb et al., 2023; Boer et al., 2018). To assess causal credibility, we report Oster's δ (Oster, 2019) and Cinelli–Hazlett robustness values (Cinelli & Hazlett, 2020), doubly robust augmented inverse-probability weighting (AIPW) for digital adoption (Chernozhukov et al., 2018), estimates with census-adjusted survey weights, logit average marginal effects and a marker-variable test for common-method variance (Baumgartner & Weijters, 2021; Podsakoff et al., 2024). To probe reverse causality, we compare entrepreneurs who were digital before the pandemic with those who adopted during it, and nascent founders with established owner-managers.

Finally, we treat the November 2022 release of ChatGPT as a global shock (Cai et al., 2025) in a continuous difference-in-differences design (Equation 2), where D is new-business density, I pre-shock digital intensity and the country-specific trend term absorbs pre-existing convergence. Event-study and placebo specifications follow recent methodological guidance (Callaway & Sant'Anna, 2021; Roth et al., 2023; Rambachan & Roth, 2023).

$$\ln(D_{ct}) = \theta(I_c \times \text{Post}_t) + \lambda(I_c \times t) + \alpha_c + \tau_t + u_{ct} \quad (2)$$

D. Data integration and quality assurance

All files were retrieved programmatically and logged with their source URL, retrieval date and SHA-256 hash. Because GEM variable names differ between waves, the waves were harmonised with year-aware matching, and every respondent was assigned an ISO-3 country code. Where Anthropic did not publish its per-capita usage index for a period, we derived it from published usage shares and Anthropic's own population file; the derived values reproduce the published ones at $r = 0.993$. No value was imputed, and 105 automated checks of row counts, value ranges, key uniqueness and merges pass.

Results

A. Descriptive patterns and the global AI divide

Entrepreneurs in emerging economies are less digitalised but no less oriented towards sustainability (Table 3). Fewer of them sell digitally (55% vs 69%), yet more plan to digitalise further, and they are as likely as their counterparts in advanced economies to take environmental steps and more likely to take social-impact steps. They also operate in far less AI-intensive environments (Figure 3): revealed AI use per working-age person is roughly 25 times higher in high-income than in low-income economies, and it closely tracks AI preparedness ($r = 0.81$).

Table 3. Descriptive statistics for GEM entrepreneurs, 2021–2022.

Variable	Emerging mean (SD)	N	Advanced mean (SD)	N
Entrepreneurial leadership (latent, z)	0.132 (0.967)	19,214	-0.090 (1.012)	28,203
Uses digital technology to sell	0.546 (0.498)	15,698	0.685 (0.464)	40,776
Adopted/enhanced digital technology	0.383 (0.486)	15,698	0.415 (0.493)	40,776
Expects more digital use	0.567 (0.495)	15,875	0.466 (0.499)	41,346
Considers environmental implications	0.769 (0.421)	11,768	0.767 (0.422)	32,561
Took environmental steps	0.529 (0.499)	11,377	0.534 (0.499)	31,450
Took social-impact steps	0.469 (0.499)	11,374	0.397 (0.489)	31,226
New product/service	0.230 (0.421)	11,993	0.245 (0.430)	32,547
New process/technology	0.220 (0.414)	11,910	0.228 (0.420)	32,440
Expects 6+ employees in 5 years	0.302 (0.459)	9,985	0.283 (0.450)	26,770
Expected job expansion (log)	0.503 (0.945)	6,789	0.302 (0.733)	20,378
Age (years)	37.167 (12.376)	26,698	42.134 (12.915)	54,537

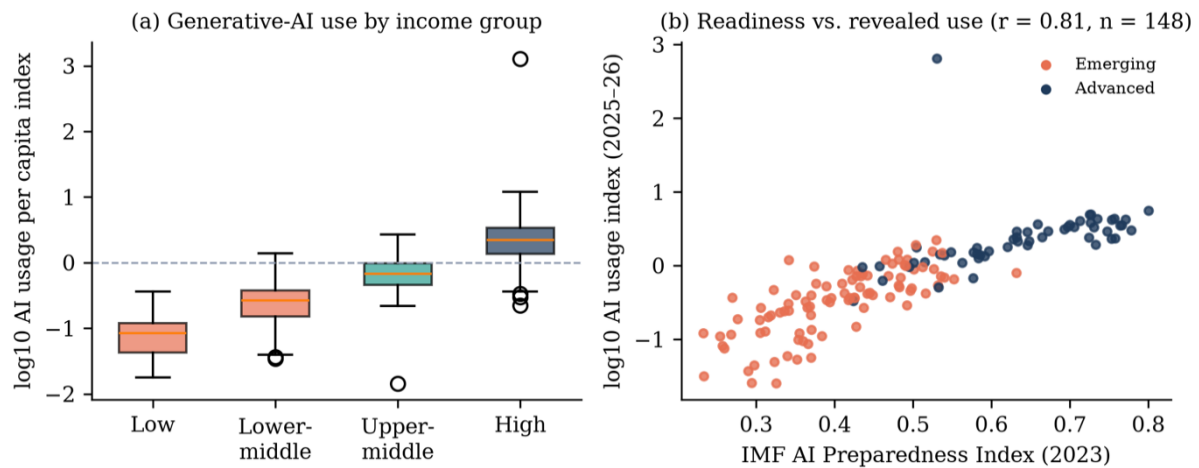


Figure 3. The global generative-AI divide: (a) usage by income group; (b) AI preparedness versus revealed use.

B. Measurement of entrepreneurial leadership

The six GEM items do not form a single factor, but they do once item wording is taken into account (Table 4). A one-factor model fits poorly ($CFI = 0.453$), whereas a leadership factor with an orthogonal factor for the three negatively worded items fits well ($M3$: $CFI = 0.973$, $RMSEA = 0.039$), and it does so in both economy groups. Self-efficacy, innovativeness, opportunity recognition and risk-taking load on the leadership factor, whereas alertness and proactiveness load almost entirely on the wording factor; these two items therefore mainly capture response style (Kam & Fan, 2020). Adding the vision motive worsens fit, so vision is modelled separately.

Multi-group analysis supports configural invariance: the same structure holds in emerging and advanced economies ($CFI = 0.973$). Constraining the loadings to equality changes $RMSEA$ by only 0.002 but lowers CFI by 0.021, beyond the conventional 0.01 threshold, so metric invariance holds only approximately (Leitgöb et al., 2023). Comparisons of leadership associations across economy groups are therefore interpreted with caution, whereas the digital-substitution results, which do not depend on the leadership measure, are unaffected.

Table 4. Confirmatory factor analysis and measurement invariance of entrepreneurial leadership.

Model	Sample	N	χ^2 (df)	CFI	TLI	RMSEA
M1 Single factor (6 items)	All	47,417	8,567.7 (9)	0.453	0.088	0.142
M1 Single factor (6 items)	Emerging	19,214	2,838.7 (9)	0.555	0.259	0.128
M1 Single factor (6 items)	Advanced	28,203	3,667.6 (9)	0.604	0.341	0.120
M2 Cognition + agency facets	All	47,417	1,456.1 (8)	0.907	0.826	0.062
M2 Cognition + agency facets	Emerging	19,214	655.1 (8)	0.898	0.809	0.065
M2 Cognition + agency facets	Advanced	28,203	720.3 (8)	0.923	0.856	0.056
M3 Single EL + wording method factor	All	47,417	433.5 (6)	0.973	0.932	0.039
M3 Single EL + wording method factor	Emerging	19,214	212.9 (6)	0.967	0.919	0.042
M3 Single EL + wording method factor	Advanced	28,203	227.1 (6)	0.976	0.940	0.036
M4 M3 + vision indicator	All	23,300	1,212.8 (11)	0.864	0.740	0.068
M4 M3 + vision indicator	Emerging	8,993	688.0 (11)	0.797	0.612	0.083
M4 M3 + vision indicator	Advanced	14,307	588.1 (11)	0.891	0.792	0.061
M3 multi-group: configural	Emerging vs advanced	47,417	440.0 (12)	0.973	0.931	0.039
M3 multi-group: metric (equal loadings) ($\Delta CFI = 0.021$)	Emerging vs advanced	47,417	778.8 (19)	0.951	0.923	0.041
M3 multi-group: scalar (equal intercepts) ($\Delta CFI = 0.009$)	Emerging vs advanced	47,417	927.6 (23)	0.942	0.924	0.041

C. Main results

Leadership is associated with digital transformation, and digital transformation with sustainable innovation and growth (Table 5). A one-standard-deviation increase in latent leadership raises the probability of digital adoption by 2.2 percentage points and that of planned digitalisation by 3.9 points (H1); leadership vision adds to both. Digital use is associated with more environmental action, more social-impact action and more product innovation (H2). Leadership, digital use, environmental steps and product innovation each predict higher expected job growth, with product innovation the strongest predictor (H3).

The structural model (Table 6) shows how these associations connect. It fits well in all groups ($CFI \geq 0.957$) and confirms that part of leadership's association with sustainable action and innovation runs through digital transformation. The route to growth runs through innovation rather than through sustainable action, so the mediation component of H3 is supported only in part.

Table 5. Country $\times$ year fixed-effects models (coefficients, clustered SE in parentheses).

Predictor	Digital adoption	Digital intention	Environmental steps	Social-impact steps	New product	Growth expectation
Entrepreneurial leadership (EL, latent)	0.022*** (0.005)	0.039*** (0.008)	0.016** (0.006)	0.028*** (0.007)	0.038*** (0.006)	0.059*** (0.015)
EL $\times$ Emerging	-0.011 (0.011)	0.004 (0.013)	0.009 (0.011)	0.005 (0.011)	-0.029** (0.010)	0.002 (0.028)
Vision motive	0.040*** (0.005)	0.059*** (0.006)	0.051*** (0.009)	0.067*** (0.009)	0.067*** (0.005)	0.036** (0.014)
Digital use (DT)			0.046* (0.018)	0.093*** (0.021)	0.064*** (0.013)	0.062* (0.024)
DT $\times$ Emerging			0.071** (0.023)	0.040 (0.025)	0.042† (0.022)	0.049 (0.050)
Environmental steps						0.051*** (0.013)
New product						0.121*** (0.027)
N	20,239	20,663	19,327	19,248	19,947	11,500
Countries	41	41	41	41	41	41
R ²	0.109	0.189	0.056	0.089	0.137	0.210

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. Controls: age, age², gender, education, business stage, sector technology; country $\times$ year fixed effects; SE clustered by country.

Table 6. Latent structural equation model by economy group (standardised coefficients, SE).

Path (standardised)	All	Emerging	Advanced
EL $\rightarrow$ DT	0.116*** (0.015)	0.104*** (0.023)	0.131*** (0.019)
EL $\rightarrow$ SI	0.068*** (0.014)	0.080*** (0.023)	0.064*** (0.018)
EL $\rightarrow$ INN	0.136*** (0.015)	0.090*** (0.023)	0.160*** (0.020)
EL $\rightarrow$ GRO	0.114*** (0.015)	0.111*** (0.024)	0.129*** (0.019)
DT $\rightarrow$ SI	0.066*** (0.009)	0.118*** (0.015)	0.034** (0.012)
DT $\rightarrow$ INN	0.105*** (0.009)	0.134*** (0.015)	0.086*** (0.012)
DT $\rightarrow$ GRO	0.045*** (0.009)	0.054*** (0.015)	0.037** (0.012)
SI $\rightarrow$ GRO	0.018* (0.009)	0.008 (0.015)	0.023* (0.011)
INN $\rightarrow$ GRO	0.056*** (0.009)	0.051*** (0.015)	0.057*** (0.012)
Indirect EL $\rightarrow$ DT $\rightarrow$ SI	0.008*** (0.001)	0.012*** (0.003)	0.004** (0.002)
Indirect EL $\rightarrow$ DT $\rightarrow$ INN	0.012*** (0.002)	0.014*** (0.003)	0.011*** (0.002)
Indirect EL $\rightarrow$ DT $\rightarrow$ INN $\rightarrow$ GRO	0.001*** (0.000)	0.001** (0.000)	0.001*** (0.000)
N	12,279	4,520	7,759
CFI	0.967	0.957	0.957
TLI	0.943	0.926	0.926
RMSEA	0.020	0.023	0.024

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. Latent SEM on country-year-demeaned data; EL measured by six items with a negative-wording method factor; standardised coefficients.

D. Robustness and causal credibility

The associations are unlikely to reflect omitted variables, sample weighting, model form or common-method bias (Table 7; Figure 4). Oster's $|\delta|$ exceeds 1.8 for every association, so unobserved confounders would need to be almost twice as influential as all observed controls to explain the estimates away. Survey-weighted and logit estimates match the baseline. Doubly robust AIPW estimates place the association between digital adoption and sustainable or innovative activity at 7 to 11 percentage points, and a marker-variable test leaves every hypothesised correlation significant. These checks strengthen, but cannot replace, causal identification.

Table 7. Robustness of key associations (Table 5 specification).

Association	FE coef.	Weighted coef.	Oster δ	RV	Logit AME	AIPW all [95% CI]	AIPW emerging [95% CI]
EL $\rightarrow$ digital adoption	0.022***	0.020***	1.8	0.028	0.019***		
Vision $\rightarrow$ digital adoption	0.040***	0.040***	3.2	0.053	0.040***		
EL $\rightarrow$ digital intention	0.039***	0.038***	2.6	0.033			
Digital use $\rightarrow$ environmental steps	0.046*	0.046*	31.0	0.018	0.074***	7.3 [4.4, 10.1]	11.2 [9.1, 13.4]
Digital use $\rightarrow$ social-impact steps	0.093***	0.088***	7.9	0.032		10.5 [7.2, 13.7]	13.4 [10.3, 16.4]
Digital use $\rightarrow$ new product	0.064***	0.072***	2.8	0.035	0.084***	8.1 [5.8, 10.4]	10.5 [7.0, 14.0]
EL $\rightarrow$ growth expectation	0.059***	0.069***	16.1	0.037			
Environmental steps $\rightarrow$ growth expectation	0.051***	0.044**	-30.6	0.036			
New product $\rightarrow$ growth expectation	0.121***	0.114***	5.8	0.041			

Note: Oster δ is the degree of selection on unobservables relative to observables needed to explain away the estimate ($|\delta| > 1$ robust; negative values mean the coefficient rises with controls). RV: Cinelli–Hazlett robustness value. AIPW in percentage points.

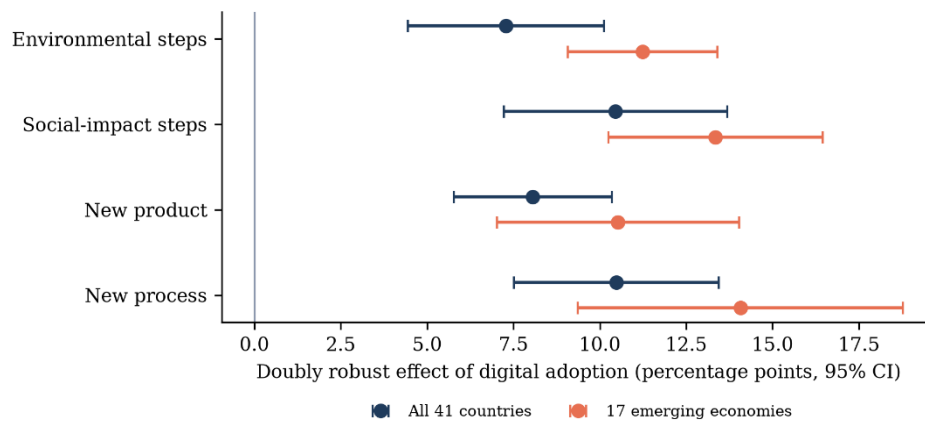


Figure 4. Doubly robust (AIPW) associations of digital adoption with sustainable and innovative outcomes.

E. Leadership of others, adoption timing and business stage

Two objections remain: that GEM's items describe individual mindsets rather than leadership of others, and that sustainable or innovative firms may digitalise rather than the reverse. Table 8 addresses both. Panels A and B re-estimate the main models for entrepreneurs who lead others those with employees or co-owners (about 14,000) and employers alone (about 10,000). The leadership associations with digital adoption and product innovation are essentially unchanged, the weaker link between leadership and product innovation in emerging economies persists, and the stronger digital-to-environmental link in emerging economies holds.

Panel C exploits the timing of digital adoption. Entrepreneurs who were already digital before the pandemic and so before the outcome window are still more likely to introduce new products (+6.1 points) and to take social-impact steps (+3.7 points), which is difficult to reconcile with reverse causation; their association with environmental steps is smaller and not significant, so that link may partly reflect concurrent change. Panel D shows that the digital associations also hold for nascent founders, who have no established routines, and that among established owner-managers the digital-to-environmental link appears only in emerging economies direct support for the substitution argument.

Table 8. Leadership of others, timing of digital adoption and business stage.

Association	Coefficient (SE)	N
A. Entrepreneurs who lead others (employees or co-owners)		
EL → digital adoption	0.024** (0.007)	13,964
EL → new product	0.039*** (0.005)	13,804
EL × emerging → new product	-0.026* (0.012)	13,804
DT → environmental steps	0.052** (0.019)	13,439
DT × emerging → environmental steps	0.060* (0.027)	13,439
DT → social-impact steps	0.095*** (0.024)	13,369
B. Employers only		
EL → digital adoption	0.021** (0.008)	10,226
EL → new product	0.043*** (0.006)	10,115
EL × emerging → new product	-0.025† (0.013)	10,115
DT → environmental steps	0.050* (0.022)	9,886
DT × emerging → environmental steps	0.085* (0.036)	9,886
DT → social-impact steps	0.100*** (0.030)	9,813
C. Timing of digital adoption (reference: no digital technology)		
Digital before the pandemic → environmental steps	0.022 (0.014)	19,327
Digital before the pandemic → social-impact steps	0.037* (0.015)	19,248
Digital before the pandemic → new product	0.061*** (0.013)	19,947
First adopted during the pandemic → environmental steps	0.100*** (0.018)	19,327
First adopted during the pandemic → social-impact steps	0.151*** (0.016)	19,248
First adopted during the pandemic → new product	0.076*** (0.015)	19,947
D. Business stage		
Nascent founders: DT → environmental steps	0.065** (0.025)	6,231
Nascent founders: DT → new product	0.076*** (0.011)	6,590
Established firms: DT → environmental steps	0.019 (0.026)	8,023
Established firms: DT × emerging → environmental steps	0.124** (0.038)	8,023

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. Table 5 specification estimated on the indicated subsamples (Panels A, B, D) or with adoption-timing indicators (Panel C); country × year fixed effects; SE clustered by country.

F. Digital substitution in emerging economies

The digital channel is markedly stronger in emerging economies (Figure 5). Digital use is associated with environmental action about 2.5 times as strongly there as in advanced economies (interaction $p = 0.002$), and the corresponding structural path is 0.118 against 0.034. The doubly robust estimates are larger in emerging economies for every outcome. Leadership shows the opposite pattern for product innovation, which it predicts less strongly in emerging economies ($p = 0.004$), although its association with environmental action is the same in both groups. The country-specific slopes in Figure 6 tell the same story: seven of the ten steepest digital-to-environmental slopes belong to emerging economies, which account for 41% of the sample. H5 is therefore supported for the digital channel and for product innovation, but not for environmental action.

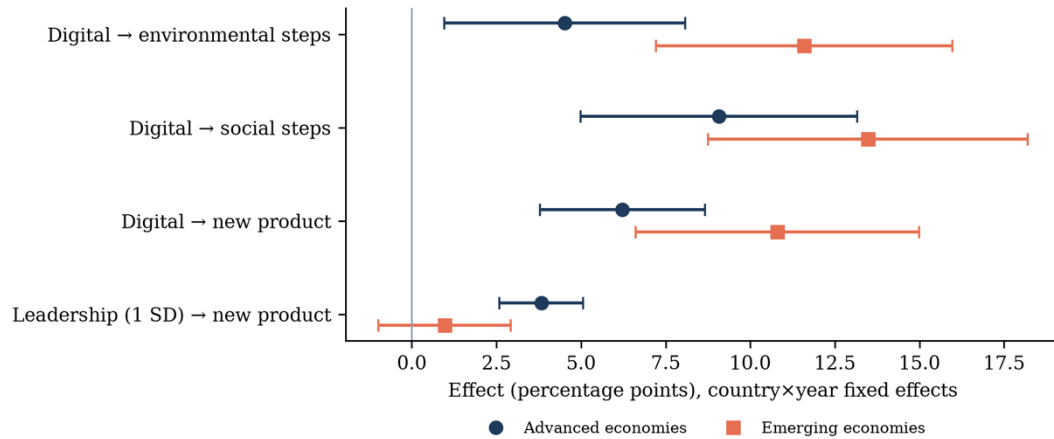


Figure 5. Digital substitution: associations in advanced versus emerging economies (95% CI).

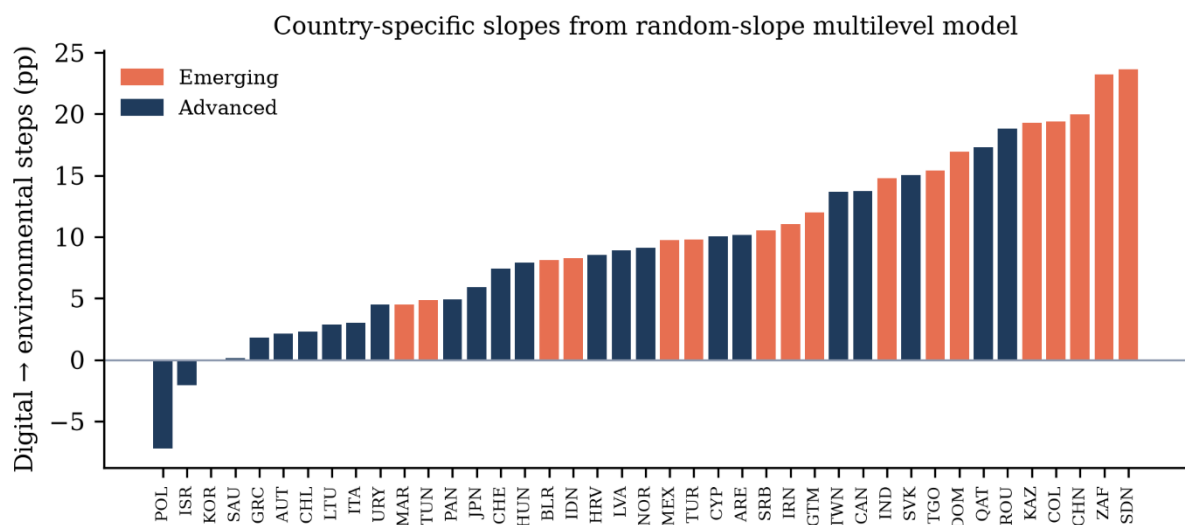


Figure 6. Country-specific digital-to-environmental-action slopes (random-slope multilevel model).

G. National AI capacity and the ChatGPT shock

National AI capacity does not amplify leadership, so H4 is not supported (Table 9): no interaction between leadership and AI preparedness, revealed AI use or developer density approaches significance. AI capacity does, however, condition the digital channel, in the direction that substitution predicts. Where AI preparedness or developer density is one standard deviation higher, the association between digital use and environmental action is about three points weaker ($p < 0.001$). Digital tools thus matter most for sustainability where national AI capacity is lowest, mirroring the emerging-economy result.

Table 9. Cross-level moderation by national AI capacity (H4).

Cross-level interaction (moderator per SD)	Coefficient (SE)	p	N	Countries
EL × IMF AI preparedness → digital adoption	0.0012 (0.0050)	0.809	20,006	40
EL × revealed AI use → digital adoption	-0.0012 (0.0041)	0.769	19,096	36
EL × developer density → digital adoption	0.0027 (0.0040)	0.492	20,006	40
EL × IMF AI preparedness → growth expectation	-0.0056 (0.0135)	0.680	11,743	40
EL × revealed AI use → growth expectation	-0.0024 (0.0131)	0.856	11,336	36
DT × developer density → environmental steps	-0.0297 (0.0089)	0.001	19,102	40
DT × IMF AI preparedness → environmental steps	-0.0334 (0.0082)	0.000	19,102	40

Note: Linear models with country × year fixed effects and the Table 5 controls; moderators standardised (AI usage and developer density in logs); SE clustered by country.

Nor did generative AI leave a detectable mark on national business entry. Naive difference-in-differences estimates suggest that more digital economies experienced slower growth in entry after ChatGPT's release (Table 10), but the 2019 placebo and the event study (Figure 7) show that this reflects a convergence trend dating back to 2015. Once the trend is controlled, the post-2022 break is close to zero for every intensity measure. Grid-level evidence from China (Cai et al., 2025) suggests that any effect may be too localised to appear in national aggregates.

Table 10. ChatGPT release and national new-business density: difference-in-differences.

Treatment intensity (per SD)	Countries	Naive DiD	Placebo 2019	Pre-trend slope	Trend-adjusted DiD	× Emerging
GitHub developers per 1,000 (2021)	117	-0.123***	-0.088*	-0.024**	-0.005 (p = 0.83)	0.113 (p = 0.49)
Internet users % (2021)	113	-0.098**	-0.081*	-0.020**	0.001 (p = 0.96)	-0.041 (p = 0.78)
ICT service exports % (2021)	111	-0.013	0.013	0.004	-0.032 (p = 0.24)	-0.019 (p = 0.72)
AI usage index (2025–26) ^a	111	-0.137***	-0.127***	-0.031***	0.015 (p = 0.65)	0.106 (p = 0.44)

Note: Outcome is log new-business density, 2015–2024; country and year fixed effects; SE clustered by country. ^a Measured after the shock; interpret as structural AI-use propensity.

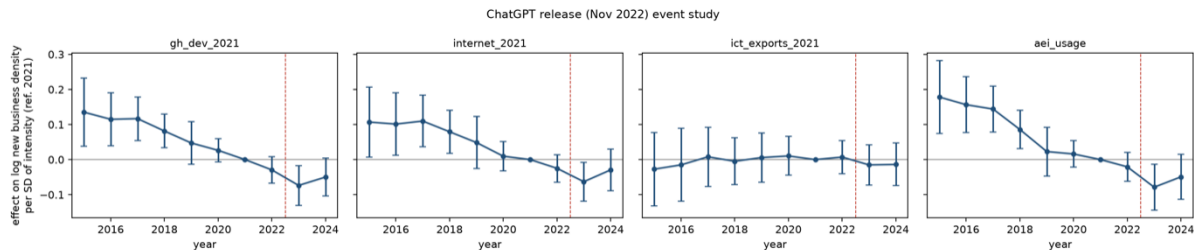


Figure 7. Event study of the ChatGPT release (reference year 2021; 95% CI).

H. Additional analyses

Two further analyses support these conclusions. Logit models reproduce the linear estimates closely, and a random-slope model shows that the digital-to-environmental slope varies widely between countries (between-country SD of 11.5 points around a mean of 6.6), so national context shapes how digital adoption translates into sustainability. At country level, revealed AI use is strongly related to AI preparedness, internet use and developer density but negatively related to early-stage entrepreneurship: the economies with the most entrepreneurs use AI least. Table 11 summarises the hypothesis tests.

Table 11. Summary of hypothesis tests.

Hypothesis	Evidence	Verdict
H1 EL → digital transformation	+2.2 pp adoption and +3.9 pp intention per SD (Table 5); holds among those who lead others (Table 8); Oster $\delta \geq 1.8$	Supported
H2a DT → environmental/social action	+4.6 and +9.3 pp (Table 5); AIPW +7.3 and +10.5 pp (Table 7)	Supported
H2b DT → product/process innovation	+6.4 pp new product (Table 5); AIPW +8.1 and +10.5 pp; holds for pre-pandemic adopters (Table 8)	Supported
H3 EL, DT, SI → growth expectations	EL +5.9%, DT +6.2%, environmental steps +5.1%, new product +12.1%; indirect path via innovation significant, via sustainable action not	Supported (mediation in part)
H4 National AI capacity amplifies EL	All EL × AI-capacity interactions ≈ 0 (Table 9)	Not supported
H5 Digital substitution in emerging economies	DT → environmental steps +7.1 pp stronger and weaker where AI capacity is high; EL → new product −2.9 pp; EL → environmental steps no difference	Supported for DT and product innovation

Discussion

Theoretical implications: The findings bear on the three contributions set out in the introduction. On measurement, the apparent unreliability of GEM's cognition items stems from item wording rather than from an incoherent construct: modelling the wording factor recovers a leadership construct with the same structure in emerging and advanced economies (Kam & Fan, 2020; Bagheri & Harrison, 2020), and its associations hold among entrepreneurs who actually lead others. On mechanism, digital transformation emerges as the channel through which leadership reaches sustainable innovation and, via innovation, growth. This extends the twin-transition literature from firms in single countries (Montesor & Vezzani, 2023; Menéndez & Lavopa, 2025) to entrepreneurs in 41 economies, and from eco-innovation to social-impact action.

On context, the evidence favours substitution over amplification. Digital tools matter more where economies are emerging and where national AI capacity is low, and leadership converts into product innovation less readily in emerging economies. These patterns are what institutional-voids theory predicts: digital technologies supply some of the information, market access and coordination that weak institutions fail to provide (Soluk et al., 2021; Heeks et al., 2021), whereas leadership capabilities depend on complementary institutions to be converted into innovation (Ge et al., 2019). National AI capacity, in turn, does not raise the returns to leadership, which suggests that AI-era advantages for entrepreneurs rest on firm-level adoption rather than on national readiness alone (Chalmers et al., 2021; Nambisan et al., 2019).

Comparison with prior evidence: The descriptive patterns are consistent with GEM's sustainability report, which finds that more than half of new entrepreneurs consider environmental implications in most economies (Hill et al., 2025); in our sample the figure is 77%. The positive association between digital adoption and environmental action agrees in direction with firm-level twin-transition evidence (Montesor & Vezzani, 2023; Menéndez & Lavopa, 2025), and the 12% association between new products and expected job growth agrees with multi-country evidence that innovation raises growth aspirations (Estrin et al., 2022). The standardised leadership paths ($\beta = 0.06$ – 0.16) are modest; because country × year effects and the wording factor remove contextual and shared-method variance, they are likely conservative relative to single-context designs (Hoang et al., 2025).

Practical and policy implications: For entrepreneurs in emerging economies, accessible digital tools offer a direct route to sustainable and innovative activity. For policymakers, programmes that help small businesses adopt digital tools are likely to yield larger sustainability dividends in emerging than in advanced economies, whereas investment in national AI readiness alone is unlikely to change entrepreneurial behaviour without accompanying capability building. Given the steep divide in AI use (Figure 3), inclusive policies on AI skills and access are needed to prevent the AI era from widening entrepreneurial gaps (Cazzaniga et al., 2024; Kulkov et al., 2024).

Boundary conditions: Leadership remains positively associated with every outcome, so digital tools complement rather than replace leadership overall; substitution appears specifically in how capabilities are converted into innovation. Moreover, the convergence of business-entry rates since 2015 cautions against attributing aggregate entry dynamics to generative AI without accounting for pre-existing trends (Roth et al., 2023; Rambachan & Roth, 2023).

Limitations and future research

Several limitations qualify the conclusions and suggest directions for future research. First, the data are cross-sectional self-reports. Fixed effects, Oster bounds, AIPW, the marker test and the timing analysis reduce but do not remove confounding, reverse causation and method bias, so the estimates are associations rather than causal effects. Second, growth is measured by expectations; linking GEM-type surveys to administrative records and would allow realised growth to be studied. Third, the digital item records the use of digital technologies for selling around the COVID-19 pandemic time rather than firm-level AI use; enterprise AI-adoption modules extended to emerging economies would close this gap.

Fourth, leadership rests on single GEM items per facet; two negatively worded items mainly capture response style, and metric invariance across economy groups holds only approximately. Embedding validated multi-item leadership scales (Bagheri & Harrison, 2020) in cross-national surveys would sharpen measurement. Fifth, the national AI measures (2023–2026) post-date the 2021–2022 survey and are interpreted as structural capacity, and only 17 emerging economies contribute complete leadership data, which limits the precision of cross-level tests. Finally, GEM individual data after 2022 were not yet available; granular registration data from emerging economies, combined with task-based measures of AI exposure (Handa et al., 2025; Eloundou et al., 2024), would allow a sharper test of whether generative AI reshapes business entry.

Conclusion

Entrepreneurial leadership matters in the AI era, but mostly through what entrepreneurs do with digital tools. Across 41 economies, leadership is associated with digital adoption, and digital adoption with sustainable action, innovation and growth expectations. This channel is strongest in emerging economies and where national AI capacity is weakest, while national AI capacity does not raise the returns to leadership. For research, the findings suggest treating AI capacity as a context that can substitute for, rather than multiply, individual capabilities. For policy, they suggest that helping small firms adopt digital tools may do more for sustainable entrepreneurship in emerging economies than investment in national AI readiness alone.

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