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Does government AI readiness translate into technological upgrading? Within–between evidence from manufacturing and exports

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Abstract. Artificial intelligence is increasingly viewed as a driver of productivity and technological transformation, yet it remains unclear whether national AI readiness translates into measurable upgrading of manufacturing and export structures. The study aims to examine how government AI readiness is associated with the technological structure of production and exports, distinguishing persistent between-country differences from short-run within-country changes and assessing prospective associations with technology-intensive manufacturing. The analysis combines the Oxford Insights Government AI Readiness Index with World Bank indicators for up to 176 countries in 2020, 2021, 2023 and 2024, applying two-way fixed effects, a within–between decomposition, non-linearity and interaction tests, ANCOVA and change-score models, and multiple robustness procedures. The core fixed-effects models show no significant

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contemporaneous GAIRI association, with coefficients ranging from 0.001 for logged ICT exports to 0.079 for high-technology exports within manufactured exports. By contrast, between-country GAIRI is positively associated with manufacturing value added ($\beta=0.180$), high-technology exports ($\beta=0.519$ and 0.491), and ICT service exports ($\beta=0.168$). Manufacturing exhibits only suggestive curvature, with a turning point of 57.59 and a formal inverted-U test of $p=0.108$. Higher 2021 GAIRI is prospectively associated with the 2023 machinery share ($\beta=0.505$, $p=0.0016$; $pBH=0.0047$).

Keywords: Government AI Readiness Index, artificial intelligence readiness, technological upgrading, manufacturing structure, high-technology exports, ICT service exports, within-between analysis.

JEL Classification: O33, O38, L60, F14

1. INTRODUCTION

Artificial intelligence is increasingly regarded not only as a digital technology but also as a potential source of productivity growth, industrial innovation and structural transformation. The World Bank (2025) emphasises that AI can increase productivity, expand market access and support the emergence of new industries, while simultaneously documenting a pronounced international AI divide: high-income economies continue to dominate AI innovation, computing capacity and start-up financing, whereas many lower-income economies face constraints related to connectivity, computing resources, locally relevant data and digital skills. The report consequently identifies connectivity, compute, context-specific data and competency as complementary foundations required for effective participation in the AI economy. Similar concerns emerge from the OECD, which characterises AI as a potential general-purpose technology capable of contributing to productivity and long-term growth but stresses that the magnitude of these gains depends on diffusion beyond leading firms and on complementary investments in digital infrastructure, organisational capabilities and human capital (Filippucci et al., 2024; OECD, 2024). These conditions are particularly relevant to manufacturing, where AI can support production optimisation, quality assurance, automation and supply-chain management, yet adoption remains comparatively limited: OECD (2026) evidence for the European Union indicates that the share of manufacturing enterprises using at least one AI technology increased from approximately 7% in 2021 to 11% in 2024, while adoption remains concentrated in particular industries and larger, more digitally capable firms.

The strategic importance of these disparities has made national AI readiness increasingly relevant to industrial and competitiveness policy. The European Commission's *AI Continent Action Plan* explicitly links AI diffusion to productivity, innovative business models, and European competitiveness, and places computing infrastructure, data, skills, and broader conditions for AI adoption at the centre of its strategy. Nevertheless, the expectation that stronger AI capabilities will translate into observable technological upgrading at the national level remains empirically unresolved. OECD assessments underline that the long-run macroeconomic productivity consequences of AI remain uncertain despite increasingly positive micro-level evidence (Filippucci et al., 2024), while the World Bank (2025) notes that AI may simultaneously create new opportunities for firms and service exports and intensify competitive pressures that make participation in global markets more difficult for less prepared economies. This creates an important distinction between AI readiness as a persistent national capability and AI readiness as a short-run driver of structural economic change. Establishing whether countries with stronger institutional, technological and data-related foundations for AI also exhibit more technology-intensive manufacturing and export structures, and

whether corresponding changes within countries follow improvements in such readiness, is therefore important for understanding how the emerging AI economy may translate into productive transformation rather than remaining concentrated in digital capacity alone.

2. LITERATURE REVIEW

The literature increasingly treats artificial intelligence readiness as a multidimensional national capability rather than simply the availability of individual AI technologies. At the macro level, the development of AI ecosystems depends on mutually reinforcing institutional, technological, data, knowledge and innovation capacities, which can shape the broader architecture of the knowledge economy and its growth potential (Abdullayev et al., 2026). This perspective is consistent with evidence that digital readiness remains unevenly distributed even among European Union countries, reflecting persistent differences in structural conditions and preparedness for Industry 5.0 (Valaskova et al., 2025). The institutional component is equally important because digital transformation requires changes in public-sector competencies, governance models and citizens' interaction with digital government, while weak institutional capacity may restrict the translation of technological opportunities into broader public benefits (Androniceanu & Streimikiene, 2025; Crăciun et al., 2025; Kafoe et al., 2026). Recent country-level research consequently extends AI readiness beyond the technology sector itself, linking government AI readiness to renewable electricity development and digital urban governance, while global evidence on AI vibrancy associates stronger AI ecosystems with changes in labour-market structures (Kuzior et al., 2025a; Kuzior et al., 2026; Lyeonov et al., 2025). At the same time, the relationship between AI development and macroeconomic performance need not be immediate or linear: evidence of an AI productivity paradox suggests that technological advances may take time to translate into measurable productivity improvements (Škare et al., 2025). Together, these studies support viewing national AI readiness as a persistent configuration of institutional and technological capabilities whose economic consequences may differ from those generated by short-term changes in readiness.

A second strand of research examines how digital and AI capabilities are translated into outcomes at the enterprise and manufacturing levels. Manufacturing adoption depends not only on access to AI but also on behavioural acceptance, organisational capability and employees' intention to use new technologies (Alhammedi, 2025). More broadly, digital transformation has been associated with financial sustainability, firm performance and organisational resilience, although these relationships can depend on firm size and complementary managerial capabilities (Al-Shouha et al., 2025; Brabete et al., 2026; Susanti et al., 2026). Studies of manufacturing digitalisation similarly emphasise that technology–organisation–environment conditions and enterprise-level digital readiness determine whether firms can adapt to ecosystem transformation and extract benefits from Industry 4.0 technologies (Ślusarczyk, 2025; Tashenova et al., 2025; Xu, 2025). AI applications can also improve project efficiency, supply-chain performance and resilience, suggesting that technological upgrading operates through changes in decision-making, coordination and production management rather than through technology acquisition alone (Golubtsov et al., 2025; Kozhakhmetova et al., 2024; Taha et al., 2025). Evidence from automobile manufacturing further highlights the role of knowledge-based leadership and AI-enabled supply-chain intelligence, while research on the Romanian automotive sector demonstrates that automation and digitalisation are embedded in broader economic and sociopolitical transformations (Kemrichard et al., 2026; Popescu et al., 2025). The emerging technological architecture of manufacturing is increasingly characterised by digital twins, cyber-physical systems, robotic technologies, extended reality and generative AI, reinforcing the idea that industrial transformation is systemic rather than reducible to a single technology (Lazaroiu et al., 2024a, 2024b). Related studies associate digitalisation and innovation with manufacturing performance and firm value and identify investment implications arising from the transition towards smart manufacturing (Rohman et al.,

2025; Tudor et al., 2026; Xue et al., 2025). The broader digital economy has likewise been connected to higher-quality manufacturing development, while financial stratification can affect firms' ability to undertake digital transformation during periods of market disruption (Sartamorn et al., 2025; Wang & Zeng, 2025).

The capacity to convert AI readiness into technological upgrading also has an explicitly human and organisational dimension, which is particularly relevant from a human-technology perspective. AI implementation in manufacturing changes the skill composition demanded of employees, as demonstrated by research in the automotive industry, while the diffusion of Industry 4.0 creates new training and awareness requirements in logistics and transport (Crețu et al., 2024; Išoraitė et al., 2026). Broader evidence shows that attitudes towards AI, perceptions of its role and organisational readiness influence how the technology is understood and adopted, including among students and future labour-market participants (Pisică & Zaharia, 2025). These human dimensions extend beyond manufacturing: AI adoption raises socioeconomic and ethical issues in law enforcement, affects research and investment processes in pharmaceutical innovation, and creates both opportunities and challenges in creative industries (Haley & Burrell, 2025; Kritikos & Sarantopoulos, 2025; Schinello, 2025). AI-driven transformation is also evident in knowledge-intensive and service settings, including publishing, telecommunications, and energy management applications, illustrating substantial sectoral heterogeneity in how technological capabilities translate into operational or economic outcomes (Olszewski & Krawczyk, 2026; Shah et al., 2025; Tomczyk et al., 2025). Cost-effectiveness considerations further affect the feasibility of AI deployment in specific organisational processes, underscoring that technological readiness does not automatically imply economically justified implementation (Kapyseva et al., 2026). More broadly, entrepreneurship, access to financial resources and firms' responses to crisis conditions shape the capacity to exploit technological opportunities, indicating that AI readiness operates within wider business and institutional ecosystems rather than independently of them (Ben, 2025; Sari & Tjahjadi, 2026). The interaction between entrepreneurship and digitalisation is especially important because the development of entrepreneurial ecosystems and digital transformation can be mutually reinforcing, creating complementary conditions for the diffusion of innovation and the commercialisation of new technologies (Mursalov et al., 2023). This literature therefore suggests that technological upgrading should be understood as a socio-technical process in which infrastructure and AI capabilities interact with skills, organisations, investment decisions and sector-specific conditions.

For the present study, the connection between technological capabilities and international specialisation is particularly important. Digital transformation and internal organisational capabilities have been linked to export performance among manufacturing SMEs, supporting the view that technological capability can strengthen firms' participation in international markets (Dinh & Tran, 2026). However, export upgrading is also conditioned by regulatory frameworks and institutional capacity, as shown by research on e-commerce-driven exports, while participation in global value chains may influence industrialisation and employment creation in developing economies (Harma et al., 2025; Mehra & Singh, 2025). International capital flows constitute another mechanism through which industrial structures evolve: foreign direct investment can affect domestic industries, while the sectoral allocation of FDI interacts with institutional conditions and broader sustainability objectives (Baghirzade et al., 2025; Popovici et al., 2026). Innovation-oriented public support can complement these private investment channels: cross-country evidence indicates that public energy R&D is associated with green entrepreneurial activity, start-up formation and venture financing, highlighting the importance of public knowledge investment in creating conditions for technology-intensive entrepreneurship (Sitnicki et al., 2026). The development of industries is likewise shaped by public-private interaction, investment, labour conditions and institutional determinants, indicating that technological transformation is embedded in a wider policy and financing environment (Topazly et al., 2025). Moreover, structural change can be accelerated or disrupted by major external shocks.

Evidence of sectoral credit reallocation after the 2022 structural break in Europe and of changes in renewable-energy investment amid heightened energy-security risks demonstrates that investment patterns and sectoral structures can shift substantially when macroeconomic and geopolitical conditions change (Vasylieva et al., 2026; Zozulinsky & Bilan, 2026). Such transformations may also exhibit nonlinear or bifurcation-type dynamics, whereby accumulated structural pressures move an economic system towards qualitatively different development trajectories rather than producing proportional incremental adjustments (Vasylieva et al., 2019). Conventional macroeconomic conditions, including inflation and labour-market developments, therefore remain relevant when evaluating technological restructuring (Senci & Afful, 2025). Sector-specific technological transitions, such as changes in cooling and air-conditioning technologies, and regulatory changes affecting responsible production, likewise illustrate that industrial upgrading may arise from multiple technological and institutional pressures rather than AI alone (Ruciński, 2024; Zhidbekkyzy et al., 2024). These findings justify accounting for macroeconomic and investment conditions when examining the conditional association between AI readiness and manufacturing and export structures.

Despite this expanding literature, a gap remains between research on national AI readiness and research on industrial technological upgrading. Existing country-level studies have primarily examined macroeconomic growth, employment, labour-market displacement, public governance, renewable energy or digital-city outcomes rather than the technological composition of manufacturing and exports (Abdullayev et al., 2026; Kuzior et al., 2025a; Lyeonov et al., 2025). Evidence that AI vibrancy can affect employment groups differently further demonstrates that the consequences of AI development are heterogeneous and depend on the outcome examined (Kuzior et al., 2025b). Similarly, government AI readiness has been associated with cities' capacity to strengthen digital governance, but this does not establish whether national readiness is reflected in productive specialisation or export sophistication (Kuzior et al., 2026). At the enterprise level, a substantial body of research demonstrates relationships between AI, digital transformation, organisational capabilities and firm-level performance, but these studies generally focus on firms, industries or individual technological applications rather than persistent national differences in AI readiness (Alhammadi, 2025; Brabete et al., 2026; Tashenova et al., 2025). Consequently, the literature does not clearly establish whether countries with stronger AI-readiness ecosystems possess systematically more technology-intensive manufacturing and export structures, or whether corresponding structural changes accompany improvements in readiness within a country. This distinction is particularly important because a strong cross-country correlation may reflect persistent differences in income, institutions, innovation systems or human capital rather than a short-run response to changes in AI readiness.

The existing scientific landscape therefore points to three connected propositions: AI readiness is a multidimensional national capability; the conversion of digital capabilities into productive outcomes depends on complementary organisational, human and institutional conditions; and technological upgrading is reflected differently across manufacturing, exports and sector-specific activities. However, previous research provides limited evidence on whether the observed association between AI readiness and technological sophistication is primarily between countries or within countries over time, and whether it is stronger for technology-intensive activities than for broader industrial shares. The present study addresses this gap by jointly examining industry and manufacturing value-added shares, high-technology export indicators and ICT service exports. At the same time, supplementary analyses examine medium- and high-technology manufacturing and the subsequent structure of machinery and transport equipment. By explicitly separating within-country changes from persistent between-country differences, the study connects the national AI-readiness literature with research on manufacturing transformation and export sophistication. It provides a more precise assessment of whether government AI readiness translates into technological upgrading.

The preceding literature suggests that national AI readiness may be linked to technological and productive transformation. However, it remains unclear whether these relationships reflect changes in AI-readiness capacity within countries or persistent structural differences between countries, and whether they are more pronounced in technology-intensive activities than in broader industrial structures. Accordingly, this study aims to examine how national government AI readiness is associated with the technological structure of production and exports across countries, distinguishing persistent between-country differences in AI readiness capacity from short-run within-country changes, and assessing whether these associations are more pronounced in technology-intensive manufacturing and export activities. To operationalise this aim, the study addresses the following research questions:

RQ1. *How is government AI readiness associated with the industrial, manufacturing and technological export structure of national economies?*

RQ2. *Do these associations primarily reflect short-run changes in AI readiness within countries or persistent differences in AI-readiness capacity between countries?*

RQ3. *Are associations with AI readiness more evident for technology-intensive manufacturing and export structures than for broader industry and manufacturing shares?*

RQ4. *Is initial government AI readiness prospectively associated with subsequent changes in technology-intensive manufacturing structure?*

3. METHODOLOGY

3.1. Data and sample construction

The study employs an unbalanced cross-country panel dataset that combines information on government readiness for artificial intelligence with indicators of industrial structure, technological specialisation, export sophistication, and macroeconomic conditions. Government AI readiness is measured using the Government AI Readiness Index (GAIRI) developed by Oxford Insights (Oxford Insights, n.d.). The index evaluates countries' capacity to adopt, govern, and support artificial intelligence. It provides an overall readiness score, along with three principal pillars (Government, Technology Sector, and Data and Infrastructure) and their underlying dimensions. The principal analytical period comprises 2020, 2021, 2023 and 2024, reflecting the availability of comparable GAIRI observations and the corresponding World Bank indicators. The year 2022 is excluded because it is missing from the assembled GAIRI dataset. Although GAIRI observations for 2025 are available, the 2025 edition incorporates methodological changes to the index's construction. Consequently, 2025 is excluded from the baseline panel and used only in a separate sensitivity analysis based on within-year standardisation. This transformation addresses differences in annual scale and distribution but does not eliminate changes in the underlying index methodology.

Industrial, technological, export and macroeconomic indicators are obtained from World Bank Open Data (World Bank, n.d.). Five variables constitute the core set of dependent variables. Industry value added and manufacturing value added are measured as percentages of GDP and therefore represent the relative importance of these sectors in the national economy rather than their absolute production scale. Technological export sophistication is captured using two alternative indicators: high-technology exports as a percentage of manufactured exports, and a constructed high-technology export intensity measure, defined as high-technology exports in current US dollars divided by total merchandise exports in current US dollars, multiplied by 100. The latter measure expresses high-technology exports relative to the overall merchandise-export base. The fifth core outcome is ICT service exports, expressed in natural logarithms as $\ln(1+ICT)$ to reduce right-skewness in the monetary series. The two high-technology export measures are treated as

alternative dependent variables because of their close conceptual and empirical relationship, rather than being entered jointly in the same specification.

Supplementary sectoral outcomes are used where data availability permits. These include the medium- and high-technology share of manufacturing value added, the medium- and high-technology share of manufactured exports, and the machinery and transport equipment share of manufacturing value added. The first two indicators are available for 2020–2021 and are therefore examined using baseline-adjusted and change-score models rather than the main multi-period panel. The machinery and transport equipment indicator is used to examine whether initial AI readiness is prospectively associated with changes in a specific technology-intensive component of manufacturing between 2021 and 2023. Because coverage of these technologically disaggregated indicators is more limited than that of the core outcomes, they are treated as supplementary analyses rather than substitutes for the principal panel models.

The baseline control set comprises logged GDP per capita, real GDP growth, gross capital formation as a percentage of GDP, foreign direct investment net inflows as a percentage of GDP, and trade openness. GDP per capita is transformed using the natural logarithm to reduce the influence of the highly skewed cross-country income distribution. Given the strong descriptive association between GAIRI and logged GDP per capita, the inclusion of income is particularly important for distinguishing the conditional association of AI readiness from broader cross-country differences in economic development. Trade openness is constructed as the sum of exports and imports of goods and services, each expressed as a percentage of GDP. Together, these covariates account for differences in economic development, cyclical conditions, investment activity, international capital exposure, and integration into international markets that may be simultaneously related to AI readiness and the analysed industrial and technological outcomes. Accordingly, the estimated GAIRI coefficients are interpreted as conditional associations after accounting for the observed level of economic development and the remaining macroeconomic controls. Observations are retained on an available-case basis for each specification; consequently, the effective sample varies across dependent variables and is reported separately for each model. Same-sample robustness tests are additionally conducted to distinguish changes in the estimated coefficients resulting from the inclusion of controls from those arising from changes in sample composition.

3.2. Baseline panel specification

The principal empirical analysis uses two-way fixed-effects (TWFE) models with country and year fixed effects. The specification is:

$$Y_{it} = \beta_1 GAIRI_{it} + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

where Y_{it} denotes one of the five core industrial or technological outcomes for country i in year t ; $GAIRI_{it}$ is the Government AI Readiness Index Overall Score; X_{it} is the vector of macroeconomic controls; α_i denotes country fixed effects; λ_t represents year fixed effects; and ε_{it} is the idiosyncratic error term. Country fixed effects absorb time-invariant national characteristics, including persistent institutional, geographical and structural differences, whereas year effects control for shocks common to all countries in a given observation year. Because identification in the TWFE models is based on changes occurring within countries over time, β_1 is interpreted as a conditional within-country association rather than a causal effect. Standard errors are clustered at the country level to allow for heteroskedasticity and serial dependence within countries. Given the short panel, with only four principal observation waves, more demanding long- T covariance estimators are not used.

The distinction between overall and within-model explanatory power is explicitly retained. Overall R^2 may be high because country and year fixed effects absorb a substantial proportion of cross-country and

temporal heterogeneity; therefore, the within-R² is additionally reported for the TWFE specifications to indicate the proportion of within-country variation explained by the time-varying regressors.

3.3. Within–between decomposition

Because strong cross-sectional relationships can coexist with weak within-country associations, the baseline models are complemented by a within–between decomposition (Mundlak-type hybrid specification). For every time-varying explanatory variable X_{it} two components are constructed: the country-specific mean $\bar{X}_i$, capturing persistent between-country differences, and the deviation from that mean $X_{it} - \bar{X}_i$, capturing within-country variation. The specification can be written as:

$$Y_{it} = \beta_W(GAIRI_{it} - \overline{GAIRI}_i) + \beta_B \overline{GAIRI}_i + \gamma'_W(X_{it} - \bar{X}_i) + \gamma'_B \bar{X}_i + \lambda_t + \varepsilon_{it}$$

Here, β_W captures the conditional association between deviations of a country's GAIRI score from its own average and changes in the dependent variable, whereas β_B captures the conditional association between persistent country-average AI readiness and cross-country differences in the outcome. Year fixed effects and country-clustered standard errors are retained. This decomposition is used to distinguish temporal from structural associations and is not interpreted as a causal identification strategy.

3.4. Non-linearity and heterogeneity

Potential non-linearity is examined by augmenting the baseline specification with a squared GAIRI term. GAIRI is mean-centred prior to constructing the quadratic term:

$$Y_{it} = \beta_1 GAIRI_{it}^c + \beta_2 (GAIRI_{it}^c)^2 + \gamma' X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}$$

Where evidence of curvature emerges, the implied turning point is calculated as

$$GAIRI_{it}^c = \overline{GAIRI} - \frac{\beta_1}{2\beta_2}$$

The location and precision of the turning point are evaluated against the GAIRI range observed in the corresponding estimation sample, and its 95% confidence interval is obtained using the delta method. In addition, a formal intersection-union endpoint-slope test is applied to assess an inverted-U pattern. For a statistically supported inverted-U relationship, the marginal slope

$$\frac{\partial Y}{\partial GAIRI} = \beta_1 + 2\beta_2 GAIRI^c$$

must be significantly positive at the lower bound of the observed GAIRI range and significantly negative at the upper bound. A joint Wald test of the linear and quadratic terms is also reported. These diagnostics prevent an interior turning point or a negative squared coefficient alone from being interpreted as sufficient evidence of an inverted-U relationship.

Heterogeneity is evaluated through interaction models. First, logged GDP per capita is used as a proxy for economic absorptive capacity, and the interaction $GAIRI \times \ln GDP_{pc}$ tests whether the contemporaneous GAIRI association varies systematically with the level of economic development. GAIRI and logged GDP per capita are mean-centred before constructing the interaction; consequently, the coefficient on centred GAIRI represents its conditional association when logged GDP per capita is at its sample mean. Second, the initial manufacturing value-added share in 2020 is used to examine whether a larger pre-existing manufacturing base conditions the association between GAIRI and high-technology export intensity. The manufacturing-base variable is likewise mean-centred, so the coefficient on centred GAIRI represents its conditional association at the sample-average manufacturing value-added share. Because the initial manufacturing measure is time-invariant within countries, its level is absorbed by the country fixed effects, while its interaction with GAIRI remains identifiable. For this specification, the

reported average marginal effect of GAIRI is calculated across the observed values of the manufacturing-base moderator rather than at a single selected moderator value, with the corresponding confidence interval reported.

3.5. Forward-looking sectoral specifications

The more disaggregated technological indicators are analysed using baseline-adjusted ANCOVA and change-score models. For the 2020–2021 medium- and high-technology outcomes, the baseline-adjusted model takes the form:

$$Y_{i,2021} = \beta \text{GAIRI}_{i,2020} + \rho Y_{i,2020} + \gamma' X_{i,2020} + \varepsilon_i$$

Including the baseline dependent variable controls for pre-existing cross-country differences in technological structure and allows β to be interpreted as a prospective conditional association between initial AI readiness and the subsequent outcome. The corresponding change-score specification is:

$$\Delta Y_i = \beta \text{GAIRI}_{i,2020} + \gamma' X_{i,2020} + \varepsilon_i$$

where $\Delta Y_i = Y_{i,2021} - Y_{i,2020}$. The same logic is applied to the machinery and transport equipment share over 2021–2023, using GAIRI in 2021 as the baseline predictor and the 2021 machinery share as the lagged outcome in the ANCOVA specification. A parsimonious version of the machinery model is additionally estimated to assess sensitivity to the full control set. Because these specifications are cross-sectional after restructuring the data into baseline/follow-up form, inference is based on HC3 heteroskedasticity-robust standard errors. These models are interpreted as forward-looking or prospective associations rather than causal effects.

3.6. Robustness and sensitivity analysis

Several additional analyses assess the stability of the findings. First, same-sample models compare GAIRI-only and fully controlled TWFE specifications using the same outcome-specific observations, thereby separating the effect of adding controls from that of sample composition. Second, variance inflation factors are calculated to assess multicollinearity, with particular attention to the strong raw association between GAIRI and GDP per capita. Third, the 2025 observations are incorporated in a sensitivity analysis after GAIRI is standardised separately within each year:

$$\text{GAIRI}_{it}^z = \frac{\text{GAIRI}_{it} - \overline{\text{GAIRI}}_t}{s_{\text{GAIRI},t}}$$

Accordingly, the coefficient on standardised GAIRI represents the conditional association corresponding to a one-standard-deviation difference in GAIRI relative to the distribution observed in the corresponding year, rather than to a one-point difference on the original GAIRI scale. This procedure addresses differences in annual scale and dispersion but does not make the revised 2025 index methodologically equivalent to earlier editions; accordingly, these models are treated only as supplementary sensitivity checks.

Fourth, the GAIRI Overall Score is replaced separately by its three principal pillars (Government, Technology Sector, and Data and Infrastructure) to determine whether the aggregate index conceals a stronger association attributable to a particular dimension of AI readiness. Fifth, potentially influential observations in GDP growth, gross capital formation, FDI and trade openness are addressed by winsorising these controls at the 1st and 99th percentiles within each outcome-specific estimation sample. GAIRI logged GDP per capita, and the dependent variables are left unchanged; the baseline and winsorised specifications use identical observations.

Finally, because the empirical design evaluates several outcomes and supplementary specifications, the focal GAIRI-related tests are subjected to Benjamini–Hochberg false-discovery-rate correction. Adjustments are performed within substantively defined families of hypotheses, including the five core TWFE tests, the within–between coefficients, quadratic terms, income interactions, prospective ANCOVA tests and change-score models. Control-variable coefficients are excluded from the multiple-testing adjustment. Both unadjusted and BH-adjusted p-values are reported to distinguish results that remain robust after accounting for multiple comparisons from findings that should be considered exploratory.

All analyses are therefore interpreted as identifying conditional statistical associations. The observational nature of the data, short time dimension, irregular observation years and possible simultaneity between institutional readiness and technological development preclude a causal interpretation of the estimated coefficients.

All calculations were performed in R version 4.4.0 (2024-04-24 ucrt), “Puppy Cup” (R Foundation for Statistical Computing), on the x86_64-w64-mingw32/x64 platform. This included data preparation and variable construction, descriptive and correlational analyses, two-way fixed-effects and within–between estimation, ANCOVA and change-score models, clustered and HC3-robust inference, variance inflation factors, non-linearity diagnostics and turning-point calculations, marginal effects, within-year standardisation, winsorisation, and Benjamini–Hochberg multiple-testing adjustments.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Descriptive evidence

The descriptive evidence indicates substantial cross-country heterogeneity in both government AI readiness and the industrial and technological outcomes considered in the study. As reported in Table A1, the GAIRI Overall Score averages 46.52 points (SD = 16.68), with values ranging from 14.62 to 88.16, indicating considerable differences in national AI readiness conditions. Similar heterogeneity is evident in the outcome variables. Industry value added averages 25.90% of GDP, whereas manufacturing value added accounts for 11.84% on average. The indicators of technological sophistication are considerably more dispersed: high-technology exports represent, on average, 10.78% of manufactured exports, while the constructed high-technology export intensity measure averages 5.56% of total merchandise exports, with a maximum of 54.63%. The comparatively large dispersion of medium- and high-technology manufacturing, medium- and high-technology exports, and machinery and transport equipment further indicates that countries differ markedly in the technological composition of their productive structures. The macroeconomic controls also display substantial heterogeneity, particularly FDI and trade openness, whose wide ranges suggest the presence of influential observations that should be considered in subsequent robustness analysis. Data availability is generally strong for core industry and manufacturing indicators, but is more limited for technologically disaggregated outcomes, as documented in Tables A2 and A3. In particular, medium- and high-technology manufacturing and export indicators are available only for 2020–2021, while coverage of machinery and transport equipment declines sharply after 2023. This supports treating these variables as supplementary outcomes rather than forcing them into the main multi-period panel specification.

The pairwise correlations reported in Table A4 and illustrated in Figure A1 provide preliminary evidence that AI readiness is much more closely associated with technological sophistication than with the industry value-added share of GDP. GAIRI is only weakly correlated with industry value added ($r=0.049$), while its association with manufacturing value added is more noticeable ($r=0.254$). By contrast, substantially stronger positive correlations are observed with high-technology exports as a share of manufactured exports ($r=0.490$), high-technology export intensity relative to total merchandise exports ($r=0.523$), and logged ICT

service exports ($r=0.805$). These patterns are consistent with the proposition that government AI readiness may be more closely connected to the technological upgrading and digitalisation of productive and export structures than to the overall share of industry in GDP. At the same time, the very strong correlation between GAIRI and GDP per capita ($r=0.852$) indicates that national AI readiness is closely intertwined with the broader level of economic development. Consequently, the multivariate analysis includes logged GDP per capita as a control, and the estimated GAIRI coefficients should be interpreted as conditional associations, accounting for differences in economic development and other macroeconomic covariates, rather than as unconditional relationships between AI readiness and the analysed outcomes. The correlation between GAIRI and trade openness is more moderate ($r=0.320$), whereas its correlations with GDP growth, gross capital formation and FDI are weak. Two additional relationships deserve attention. First, high-technology exports as a share of manufactured exports and the newly constructed high-technology export intensity measure are highly correlated ($r=0.854$), confirming that they capture closely related dimensions of export sophistication and should therefore be modelled as alternative dependent variables rather than included simultaneously on the right-hand side of a regression. Second, the correlation between GAIRI and logged ICT service exports ($r=0.805$), together with the sizeable correlation between ICT exports and GDP per capita ($r=0.625$), reinforces the need to interpret the GAIRI association conditionally after accounting for the broader level of economic development in the fixed-effects and within-between specifications.

The temporal distribution of GAIRI further supports using the 2020–2024 period as the principal analytical window while controlling for year-specific shocks. As shown in Table A5 and Figure A2, the mean GAIRI Overall Score increased from 44.2 in 2020 to 47.4 in 2021, declined moderately to 46.0 in 2023, and subsequently rose to 48.4 in 2024. Median values exhibit a similar, although not completely monotonic, pattern, increasing from 39.6 in 2020 to 43.9 in 2024. The standard deviation remains relatively stable but rises slightly from 15.9 to 17.2, indicating that the overall improvement in average AI readiness was not accompanied by convergence across countries. The boxplots in Figure A2 likewise demonstrate persistent cross-country dispersion throughout the period and substantial overlap between annual distributions, supporting the use of country fixed effects to exploit within-country variation and year fixed effects to absorb common temporal shifts. Missingness in the GAIRI measure is limited: only 21 of the 704 potential country-year observations in the four-year analytical sample are unavailable, representing approximately 3% of observations. Missing values are concentrated primarily in 2021 (16 countries), compared with 4 in 2020, none in 2023, and 1 in 2024. Although this level of missingness is unlikely to undermine the overall panel structure, the unequal availability of the outcome and control variables documented in Tables A2 and A3 means that the effective estimation sample should be reported separately for every regression and that comparisons between unadjusted and fully controlled specifications should, where possible, also be performed on identical samples.

4.2. Baseline panel estimates

The two-way fixed-effects estimates reported in Table 1 show that, conditional on logged GDP per capita, the remaining macroeconomic controls, country fixed effects, and common year-specific shocks, the GAIRI Overall Score is not significantly associated with any of the five core industrial and technological outcomes. The estimated coefficients of GAIRI are positive in all specifications (0.008 for industry value added, 0.022 for manufacturing value added, 0.079 for high-technology exports as a share of manufactured exports, 0.004 for high-technology exports relative to merchandise exports, and 0.001 for logged ICT service exports). Still, none reach conventional levels of statistical significance. This result is particularly noteworthy when compared with the descriptive correlations reported earlier, where GAIRI was strongly correlated with high-technology export intensity ($r=0.523$) and especially with ICT service exports ($r=0.805$). The attenuation of these relationships in the fixed-effects models indicates that the positive bivariate associations

are largely attributable to persistent differences between countries rather than to short-term changes in AI readiness within the same country. Thus, the present estimates do not provide evidence that an increase in a country's GAIRI score over the relatively short observation period is accompanied by an immediate increase in the industry value-added share of GDP or technological export intensity. This finding also reinforces the rationale for the subsequent within-between decomposition, which explicitly separates within-country GAIRI variation from persistent between-country differences.

Table 1

Government AI readiness and industrial and technological outcomes: two-way fixed-effects estimates

Variables	Industry VA	Manufacturing VA	High-tech / manufactured exports	High- tech/merchandise exports	ICT service exports
GAIRI Overall Score	0.008 (0.033)	0.022 (0.016)	0.079 (0.074)	0.004 (0.030)	0.001 (0.009)
ln GDP per capita	-2.302 (5.667)	-3.270* (1.510)	11.640† (6.634)	4.876 (3.536)	1.607* (0.649)
GDP growth	0.043 (0.052)	0.012 (0.015)	-0.205* (0.101)	-0.085 (0.051)	-0.011* (0.005)
Gross capital formation	-0.016 (0.056)	-0.007 (0.019)	-0.002 (0.125)	-0.090 (0.073)	0.002 (0.009)
FDI	-0.004 (0.003)	-0.000 (0.001)	-0.012 (0.014)	-0.014† (0.009)	0.000 (0.000)
Trade openness	0.005 (0.019)	0.006 (0.007)	0.038 (0.040)	0.013 (0.016)	0.006 (0.005)
Observations	588	571	509	513	553
R ²	0.969	0.984	0.923	0.967	0.975
Adjusted R ²	0.958	0.978	0.891	0.953	0.966
Within R ²	0.010	0.030	0.046	0.061	0.025
Adjusted within R ²	-0.004	0.015	0.031	0.045	0.010
RMSE	1.71	0.74	3.54	1.77	0.46
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Source: Authors' results. Country-clustered standard errors are reported in parentheses within the same cells as the corresponding coefficient estimates. Industry VA and Manufacturing VA are measured as percentages of GDP. High-tech / manufactured exports denotes high-technology exports as a percentage of manufactured exports; High-tech/merchandise exports denotes high-technology exports relative to total merchandise exports; ICT service exports are expressed in logarithmic form. All models include country and year fixed effects. Significance codes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Among the controls, economic development and short-run macroeconomic dynamics show several statistically significant associations, although these differ across outcomes. A higher level of GDP per capita is negatively associated with manufacturing value added as a share of GDP ($\beta = -3.270$, $p < 0.05$), suggesting that within-country income growth may coincide with a relative structural shift away from manufacturing in GDP. At the same time, GDP per capita is positively associated with high-technology exports as a share of manufactured exports ($\beta = 11.640$, $p < 0.10$) and with logged ICT service exports ($\beta = 1.607$, $p < 0.05$), which is consistent with technological and digital upgrading accompanying higher levels of economic development even when the manufacturing share itself declines. GDP growth is negatively associated with both the high-technology share of manufactured exports ($\beta = -0.205$, $p < 0.05$) and ICT service exports ($\beta = -0.011$, $p < 0.05$). In contrast, FDI exhibits a weak negative association with high-technology exports relative to total merchandise exports ($\beta = -0.014$, $p < 0.10$). Gross capital formation and trade openness do not display statistically significant coefficients in any of the five models. The models have very high overall R² values,

ranging from 0.923 to 0.984, but much lower within- R^2 values of 0.010–0.061. This contrast indicates that most of the explanatory power comes from country and year fixed effects. In contrast, the observed time-varying covariates explain only a modest share of within-country variation in the dependent variables. Accordingly, the high overall R^2 should not be interpreted as evidence that GAIRI or the included controls account for most short-run changes in the analysed industrial and technological outcomes.

4.3. Within–between decomposition

The within–between decomposition (Mundlak-type hybrid specification) reported in Table 2 clearly distinguishes between short-run within-country changes in government AI readiness and persistent cross-country differences in AI readiness. Across all five outcomes, the within-country component of GAIRI (GAIRI_W) is statistically insignificant. The estimated coefficients are 0.014 for industry value added, 0.004 for manufacturing value added, 0.057 for high-technology exports as a share of manufactured exports, -0.005 for high-technology exports relative to merchandise exports, and 0.002 for logged ICT service exports. This pattern is consistent with the earlier two-way fixed-effects results. It indicates that, over the 2020–2024 analytical period, deviations of a country's GAIRI score from its country-specific mean are not systematically associated with corresponding changes in the analysed industrial and technological outcomes. Given the limited temporal variation in GAIRI and the short, irregularly spaced panel, these estimates should be interpreted as within-country associations over the observed period rather than as evidence of short-run causal effects.

By contrast, the between-country component of GAIRI (GAIRI_B) shows a stronger and more systematic relationship with technologically intensive outcomes. Conditional on the within- and between-country components of logged GDP per capita and the remaining macroeconomic controls, as well as year fixed effects, higher country-average GAIRI is positively associated with the manufacturing value-added share ($\beta=0.180$, $p<0.05$), high-technology exports as a share of manufactured exports ($\beta=0.519$, $p<0.001$), high-technology export intensity relative to merchandise exports ($\beta=0.491$, $p<0.001$), and logged ICT service exports ($\beta=0.168$, $p<0.001$). No statistically significant between-country association is observed for total industry value added ($\beta = -0.111$). These coefficients should therefore be interpreted as conditional associations with AI readiness after accounting for the observed level of economic development and the other macroeconomic covariates, rather than as unconditional differences between richer and poorer economies. The contrast between statistically insignificant within-country coefficients and significant positive between-country coefficients for several technology-intensive outcomes suggests that the relationship between AI readiness and technologically sophisticated manufacturing and export structures is concentrated primarily in persistent cross-country differences, rather than in short-run changes occurring within countries over the observed period.

This distinction also helps reconcile the strong descriptive correlations between GAIRI and technological outcomes with the insignificant GAIRI coefficients obtained from the country fixed-effects models. Conditional on the observed level of economic development and the remaining macroeconomic covariates, countries characterised by persistently higher levels of AI readiness also tend to exhibit more technologically sophisticated manufacturing and export structures. In contrast, changes in GAIRI within the same country over the relatively short analytical period are not systematically associated with contemporaneous industrial upgrading. The ICT service-export specification has the highest overall model fit ($R^2=0.709$); however, because the models employ different dependent variables and somewhat different estimation samples, differences in R^2 should not be interpreted as evidence that the GAIRI association is intrinsically stronger for ICT exports than for the other outcomes. Given the strong correlation between GAIRI and logged GDP per capita, however, these between-country coefficients should be interpreted

cautiously as conditional associations rather than as evidence that AI readiness operates independently of broader economic development.

Table 2
Within- and between-country associations between GAIRI and industrial and technological outcomes

Variable	Industry VA	Manufacturing VA	High-tech / manufactured exports	High- tech/merchandise exports	ICT service exports
GAIRI within- country (GAIRI_W)	0.014 (0.035)	0.004 (0.018)	0.057 (0.072)	−0.005 (0.037)	0.002 (0.009)
GAIRI between- country (GAIRI_B)	−0.111 (0.120)	0.180* (0.071)	0.519*** (0.144)	0.491*** (0.102)	0.168*** (0.020)
Observations	588	571	509	513	553
R ²	0.118	0.113	0.337	0.394	0.709
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Country-clustered SE	Yes	Yes	Yes	Yes	Yes

Source: The table reports estimates from a within–between decomposition (Mundlak-type hybrid specification) with year fixed effects and country-clustered standard errors. GAIRI_W is defined as the deviation of GAIRI from the country-specific mean calculated over the observations included in each estimation sample and therefore captures the within-country association. GAIRI_B is the corresponding country-specific mean, capturing the conditional between-country association. The same decomposition is applied to the time-varying macroeconomic controls. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.4. Non-linearity and heterogeneity

The non-linear specifications reported in Table B1 provide little evidence that the association between government AI readiness and the analysed industrial and technological outcomes is systematically non-linear. For the industry value-added share, high-technology exports as a share of manufactured exports, high-technology exports relative to merchandise exports, and ICT service exports, neither the linear GAIRI term nor its squared term is statistically significant. The estimated quadratic coefficients are also small in magnitude: 0.0006 for the industry value-added share, −0.0041 for high-technology exports as a share of manufactured exports, −0.0003 for high-technology export intensity relative to merchandise exports, and 0.0001 for ICT service exports. Thus, introducing a quadratic term does not reveal a statistically robust U-shaped or inverted-U association for these outcomes. The within-R² values remain low, ranging from 0.010 for the industry value-added share to 0.061 for high-technology export intensity, indicating that the quadratic specifications explain only a limited proportion of within-country variation. These findings are therefore consistent with the baseline fixed-effects results and provide no evidence that short-run within-country changes in GAIRI over the 2020–2024 analytical period are systematically associated with contemporaneous changes in the industry value-added share or the technological composition of exports and ICT services.

The manufacturing value-added share provides the only indication of possible curvature. The coefficient on centred GAIRI is positive but statistically insignificant ($\beta = 0.0246$), whereas the squared term is negative and only marginally significant ($\beta = -0.0011$, $p = 0.077$). The implied turning point is 57.59 GAIRI points and lies within the range observed in the manufacturing estimation sample (19.74–88.16); its delta-method 95% confidence interval, 38.46–76.71, also remains within this range. Although these features are consistent with a concave relationship, the formal endpoint-slope test does not confirm a statistically established inverted-U pattern. At the lower GAIRI bound, the estimated slope is positive and statistically

significant (slope = 0.084, SE = 0.037, one-sided $p=0.012$), whereas at the upper bound it is negative but statistically insignificant (slope = -0.068 , SE = 0.055, one-sided $p=0.108$). Consequently, the formal intersection-union inverted-U test yields $p=0.108$. The joint Wald test of the linear and quadratic GAIRI terms is likewise only marginally significant ($F=2.83$, $p=0.062$), and the quadratic term does not remain significant after the Benjamini–Hochberg multiple-testing adjustment ($p_{BH}=0.384$). Accordingly, the manufacturing specification should be interpreted as providing suggestive evidence of curvature rather than evidence of a statistically established inverted-U association between AI readiness and the manufacturing value-added share.

The heterogeneity analysis reported in Table B2 provides no evidence that economic absorptive capacity, proxied by logged GDP per capita, systematically conditions the within-country association between GAIRI and the five outcomes. Because GAIRI and logged GDP per capita are mean-centred before constructing the interaction, the reported coefficient on centred GAIRI in each specification represents the conditional GAIRI association at the sample-average level of logged GDP per capita. The interaction between GAIRI and logged GDP per capita is statistically insignificant for the industry value-added share ($\beta=-0.011$), high-technology exports as a share of manufactured exports ($\beta=0.006$), high-technology export intensity relative to merchandise exports ($\beta=0.034$), and ICT service exports ($\beta\approx 0.000$). The interaction coefficient indicates how the conditional GAIRI association changes as logged GDP per capita departs from its sample mean. None of these interaction terms is statistically significant, and they also remain insignificant after adjustment for multiple testing. Thus, there is no evidence that the contemporaneous within-country association between GAIRI and the analysed outcomes systematically varies with the level of economic development. Taken together, the non-linearity and heterogeneity analyses reinforce rather than overturn the main fixed-effects finding: over the relatively short observation period, changes in government AI readiness are not systematically associated with contemporaneous changes in the core industrial and technological outcomes.

The alternative moderation test based on the initial manufacturing base reaches a similar conclusion. As shown in Table B3, the interaction between centred GAIRI and manufacturing value added in 2020 is negative but not statistically significant in the high-technology merchandise-export model ($\beta = -0.0079$, SE = 0.0072, $p = 0.272$). Thus, there is no evidence that the conditional association between within-country changes in GAIRI and high-technology export intensity is systematically stronger in countries with a larger pre-existing manufacturing sector. Because the manufacturing-base moderator is mean-centred, the coefficient on centred GAIRI represents its conditional association at the sample-average 2020 manufacturing value-added share. The interaction coefficient is negative but not statistically significant ($\beta = -0.0079$, SE = 0.0072, $p = 0.272$), providing no evidence that the GAIRI association varies systematically with the size of the initial manufacturing base. When the conditional marginal effects are evaluated across all observed moderator values and averaged over the estimation sample, the average marginal effect of GAIRI on high-technology export intensity is essentially zero ($dy/dx=0.00083$, SE = 0.0301, $p=0.978$; 95% CI: -0.058 to 0.060), as reported in Table B4. The non-linearity and moderation exercises reinforce rather than overturn the earlier findings: the principal empirical distinction remains between statistically insignificant short-run within-country GAIRI associations and the strong positive between-country associations identified in the within–between decomposition. The results, therefore, suggest that technological upgrading is associated more strongly with persistent national AI-readiness configurations than with immediate changes in GAIRI, and neither income-based absorptive capacity nor the initial manufacturing base provides evidence of a systematic conditioning effect over the short observation period.

4.5. Forward-looking sectoral evidence

The baseline-adjusted ANCOVA estimates reported in Table B5 show that medium- and high-technology manufacturing structures are highly persistent over the short 2020–2021 interval. The 2020 share of manufacturing value added in medium- and high-technology is an exceptionally strong predictor of its 2021 level ($\beta=0.967$, $p<0.001$), while the corresponding persistence coefficient for medium- and high-technology exports is similarly large ($\beta=0.945$, $p<0.001$). After conditioning on these initial levels and the macroeconomic controls, the 2020 GAIRI score is not associated with subsequent medium- and high-technology manufacturing value added ($\beta = -0.011$, $p = 0.805$). For medium- and high-technology exports, however, GAIRI has a positive coefficient of 0.107 that is marginally significant at the 10% level ($p=0.093$). This provides only tentative evidence that countries entering the period with higher government AI readiness subsequently maintained or achieved a somewhat stronger high-technology orientation of manufactured exports, conditional on their initial export structure. Logged GDP per capita is also weakly negatively associated with the 2021 medium- and high-technology export share ($\beta = -1.435$, $p = 0.083$). In contrast, GDP growth, gross capital formation, FDI, and trade openness are not statistically significant in either ANCOVA specification. The dominant result is the strong persistence of pre-existing technological manufacturing and export structures rather than a pronounced one-year response to differences in AI readiness.

The change-score models in Table B6 provide a stricter robustness test and further qualify the weak ANCOVA evidence for high-technology exports. GAIRI in 2020 is not significantly associated with the 2020–2021 change in medium- and high-technology manufacturing value added ($\beta=-0.038$, $p=0.214$) or with the change in the medium- and high-technology export share ($\beta=0.060$, $p=0.253$). Thus, although the positive GAIRI coefficient in the export ANCOVA is suggestive, it is not replicated when the dependent variable is expressed as a year-to-year change. Logged GDP per capita again shows a weak negative association with the change in the medium- and high-technology export share ($\beta = -1.502$, $p = 0.082$), while none of the remaining macroeconomic controls is statistically significant. With an identical effective sample of 130 countries across all four specifications, differences between the ANCOVA and change-score results cannot be attributed to changes in sample composition. These findings support a cautious interpretation: AI readiness may be associated with persistent cross-country differences in technological export orientation, as shown more clearly by the earlier within–between decomposition, but the 2020–2021 data do not provide robust evidence that higher initial GAIRI scores were associated with measurable one-year improvements in the medium- and high-technology manufacturing and export shares.

The machinery and transport equipment results provide the clearest forward-looking evidence that government AI readiness is associated with subsequent changes in the technological composition of manufacturing. As reported in Table 3, the baseline-adjusted ANCOVA model indicates that the 2021 GAIRI score is positively and statistically significantly associated with the share of machinery and transport equipment in manufacturing value added in 2023 ($\beta = 0.505$, $p = 0.0016$). Conditional on the initial machinery share and the macroeconomic controls, a one-point increase in the GAIRI score in 2021 is associated with approximately a 0.50 percentage-point increase in the machinery and transport equipment share in 2023. The baseline machinery share is itself strongly persistent ($\beta=0.700$, $p<0.001$), indicating substantial continuity in manufacturing structure. Logged GDP per capita has a statistically significant negative association with the 2023 machinery share ($\beta = -3.351$, $p = 0.0178$), whereas GDP growth, gross capital formation, FDI, and trade openness are not statistically significant.

The positive GAIRI association is also observed in the change-score specification, in which a higher 2021 GAIRI score is associated with a larger increase in the machinery and transport equipment share between 2021 and 2023 ($\beta=0.350$, $p=0.021$). The estimate is similarly stable in the parsimonious ANCOVA specification, where the GAIRI coefficient remains virtually unchanged at 0.502 ($p=0.0016$). Moreover, the

baseline-adjusted ANCOVA association remains statistically significant after the Benjamini–Hochberg multiple-testing correction ($p_{BH}=0.0047$), whereas the change-score result is attenuated to suggestive significance ($p_{BH}=0.0641$). These results indicate statistical robustness to multiple-testing adjustment, but should be interpreted in light of the restricted sample size. The consistency of the baseline-adjusted and reduced-control estimates indicates that the positive GAIRI coefficient is reasonably stable across these alternative specifications. Nevertheless, the machinery analysis is based on only 76 countries, and the fully adjusted ANCOVA specification includes several covariates relative to this sample size. The estimates should therefore be interpreted with caution, as the limited sample size may reduce precision and increase sensitivity to model specification and individual observations. Accordingly, the result is best viewed as evidence of a prospective conditional association between AI readiness and the subsequent share of machinery and transport equipment within this restricted sample, rather than as a precisely estimated or causal relationship.

4.6. Robustness checks

The same-sample robustness analysis reported in Table B7 confirms that the core GAIRI findings are not attributable to sample attrition following the introduction of the macroeconomic controls. For each of the five outcomes, the GAIRI-only and fully controlled specifications are estimated on the same observations, with sample sizes ranging from 509 observations for high-technology exports as a share of manufactured exports to 588 observations for the industry value-added share. The GAIRI coefficient remains statistically insignificant in both specifications across all outcomes. The estimated coefficient changes only modestly after the introduction of controls: from 0.003 to 0.008 for the industry value-added share, from 0.013 to 0.022 for the manufacturing value-added share, from 0.081 to 0.079 for high-technology exports within manufactured exports, from 0.004 to 0.005 for high-technology exports relative to merchandise exports, and from 0.003 to 0.001 for logged ICT service exports. Thus, the absence of a contemporaneous within-country GAIRI association across the five core outcomes cannot be attributed to changes in sample composition caused by the inclusion of additional covariates.

Table 3

GAIRI and subsequent machinery and transport equipment performance, 2021–2023

Variable	ANCOVA: Machinery share 2023	Change in machinery share, 2021–2023	Reduced ANCOVA
GAIRI, 2021	0.505** (0.153)	0.350* (0.149)	0.502** (0.153)
Machinery share, 2021	0.700*** (0.111)	–	0.714*** (0.108)
ln GDP per capita, 2021	–3.351* (1.380)	–3.426* (1.688)	–3.447* (1.360)
GDP growth, 2021	–0.085 (0.181)	–0.103 (0.196)	–
Gross capital formation, 2021	0.124 (0.135)	–0.027 (0.158)	–
FDI, 2021	0.016 (0.076)	0.014 (0.147)	–
Trade openness, 2021	–0.008 (0.016)	–0.015 (0.017)	–0.005 (0.015)
Observations	76	76	76
Robust standard errors	HC3	HC3	HC3

Source: Authors' results. Coefficients are reported with HC3 heteroskedasticity-robust standard errors in parentheses. The first model explains the 2023 share of machinery and transport equipment conditional on its 2021 level. The

second model uses the change in the machinery share between 2021 and 2023 as the dependent variable. The reduced ANCOVA specification retains GAIRI, the baseline machinery share, logged GDP per capita and trade openness. *Given the effective sample size of 76 countries and the number of covariates in the fully adjusted specifications, the estimates should be interpreted with caution; the reduced ANCOVA model is reported as a sensitivity check for specification dependence.* Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The inclusion of the controls nevertheless increases the within R² in all five specifications, most notably from virtually zero to 0.061 for high-technology export intensity, from 0.003 to 0.046 for high-technology exports as a share of manufactured exports, and from 0.002 to 0.030 for the manufacturing value-added share. This indicates that the macroeconomic covariates contribute to explaining within-country variation in the outcomes, but their inclusion does not materially alter the estimated GAIRI association. The consistency of the GAIRI coefficients across identical samples therefore strengthens the interpretation of the baseline two-way fixed-effects results.

The robustness analysis confirms the main empirical pattern obtained from the baseline specifications. The multicollinearity diagnostics reported in Table B8 indicate some degree of overlap between GAIRI and logged GDP per capita, with VIF values of 4.37 and 4.88, respectively, while the remaining regressors have VIF values close to one. The corresponding tolerance values are 0.229 for GAIRI and 0.205 for logged GDP per capita. Because VIF thresholds are heuristic rather than universal, these values should not be interpreted as definitive evidence of multicollinearity. Instead, they indicate moderate collinearity between AI readiness and income, warranting caution when interpreting their separate coefficients. At the same time, the diagnostics do not indicate severe multicollinearity across the full set of regressors, and the stability of the GAIRI estimates across the same sample, and other robustness specifications, reduces concern that the principal results are driven primarily by multicollinearity.

The same-sample comparison for the manufacturing value-added share provides an additional robustness check. Using an identical set of 571 observations, the GAIRI coefficient remains statistically insignificant both in the specification that includes GAIRI with country and year fixed effects ($\beta = 0.013$, $SE = 0.017$) and after adding the macroeconomic controls ($\beta = 0.022$, $SE = 0.016$). The inclusion of the controls increases the within-R² from 0.002 to 0.030, indicating greater explanatory power for within-country variation in the manufacturing value-added share. However, it does not materially alter the estimated GAIRI association. Thus, the absence of a statistically significant contemporaneous within-country relationship between AI readiness and the manufacturing value-added share cannot be attributed to changes in sample composition resulting from the inclusion of additional covariates.

As an additional sensitivity analysis, the panel was extended to 2025, and GAIRI was standardised separately within each year (Table B9). This transformation reduces differences in the index's scale and annual distribution but does not eliminate changes to the underlying GAIRI methodology introduced in 2025; accordingly, the 2025 observations are excluded from the principal analytical sample. In this supplementary specification, a one-standard-deviation difference in GAIRI relative to the corresponding year-specific distribution is associated with a 0.129 percentage-point difference in the industry value-added share ($SE = 0.413$) and a 0.336 percentage-point difference in the manufacturing value-added share ($SE = 0.232$); neither association is statistically significant. These coefficients are expressed in annual standard-deviation units and therefore should not be interpreted as the association corresponding to a one-point change in the original GAIRI scale. Thus, the inclusion of 2025 does not alter the qualitative conclusion of the baseline analysis. However, these estimates should be interpreted strictly as a sensitivity check rather than as fully comparable extensions of the 2020–2024 models.

The decomposition of GAIRI into its three principal pillars provides no evidence that the insignificant aggregate relationship conceals a stronger short-run association attributable to a specific component of AI

readiness. In the high-technology export-intensity specifications reported in Table B10, the coefficients for Government ($\beta=0.011$, $SE = 0.015$), Technology Sector ($\beta=-0.070$, $SE = 0.067$), and Data and Infrastructure ($\beta=0.002$, $SE = 0.019$) are all statistically insignificant after accounting for the macroeconomic controls and country and year fixed effects. The within-R² values are also very similar across the three models, ranging from 0.061 to 0.066. Consequently, after accounting for logged GDP per capita, the remaining macroeconomic controls, and country and year fixed effects, none of the individual GAIRI pillars shows a statistically significant conditional contemporaneous association with high-technology export intensity. The robustness evidence is consistent with the earlier within-between decomposition: the empirical relationship between AI readiness and the analysed technological outcomes is concentrated primarily in persistent structural differences across countries rather than short-term within-country changes. The 2021–2023 machinery and transport equipment results remain the principal exception, providing the clearest evidence that higher initial AI readiness is associated with a subsequent increase in the machinery and transport equipment share within manufacturing.

The multiple-testing adjustment reinforces the interpretation of the preceding results without materially changing their overall pattern. As reported in Table B11, none of the five GAIRI coefficients from the core two-way fixed-effects specifications is statistically significant after applying the Benjamini–Hochberg false-discovery-rate correction, further supporting the absence of a detectable contemporaneous within-country association between GAIRI and the principal industrial and technological outcomes. In contrast, the main between-country associations remain statistically robust. Higher country-average GAIRI continues to be positively associated with the manufacturing value-added share ($pBH=0.0149$), high-technology exports as a share of manufactured exports ($pBH=0.0007$), high-technology export intensity relative to merchandise exports ($pBH<0.0001$), and logged ICT service exports ($pBH<0.0001$). Thus, the multiple-testing adjustment strengthens the evidence that the principal relationship between AI readiness and technological sophistication is concentrated in persistent cross-country differences rather than contemporaneous within-country variation.

The correction also further qualifies the weaker findings from the supplementary specifications. For the manufacturing value-added share, the quadratic GAIRI term changes from an unadjusted $p=0.0768$ to $pBH=0.3840$, providing no robust evidence of non-linearity after accounting for multiple testing and reinforcing the interpretation of the previously identified curvature as exploratory rather than as a statistically established inverted-U relationship. Likewise, none of the interactions between GAIRI and logged GDP per capita is statistically significant after adjustment, providing no evidence that the contemporaneous association between GAIRI and the analysed outcomes systematically varies with the level of economic development. Among the prospective specifications, however, the association between the 2021 GAIRI score and the machinery and transport equipment share in 2023 remains statistically significant after correction ($pBH=0.0047$). By contrast, the marginal association between 2020 GAIRI and the medium- and high-technology export share in 2021 does not survive the adjustment ($pBH=0.1389$), while the machinery change-score result is attenuated from $p=0.0214$ to $pBH=0.0641$ and therefore remains only suggestive at the 10% level. The false-discovery-rate correction sharpens the empirical distinction between the robust between-country technological associations and the prospective machinery result, on the one hand, and the generally insignificant contemporaneous, non-linear and moderating relationships, on the other.

The outlier robustness analysis reported in Table B12 confirms that the baseline estimates are not sensitive to extreme values in the macroeconomic controls. Winsorising GDP growth, gross capital formation, FDI and trade openness at the 1st and 99th percentiles produces only marginal changes in the GAIRI coefficients across all five core outcomes. The coefficient changes from 0.0077 to 0.0071 for the industry value-added share, from 0.0219 to 0.0218 for the manufacturing value-added share, from 0.0787 to 0.0781 for

high-technology exports as a share of manufactured exports, from 0.0045 to 0.0036 for high-technology exports relative to merchandise exports, and from 0.0011 to 0.0013 for logged ICT service exports. None of the GAIRI coefficients is statistically significant in either the baseline or the winsorised specification. Because each pair of models is estimated on the same outcome-specific sample, the comparison isolates the effect of treating extreme values. Changes in sample composition do not confound it.

The model-fit statistics are similarly stable following winsorisation. Within- R^2 increases modestly for the manufacturing value-added share, from 0.030 to 0.035, and for high-technology exports as a share of manufactured exports, from 0.046 to 0.058, while small declines are observed for the industry value-added share, high-technology export intensity and ICT service exports. These changes are insufficient to alter the substantive interpretation of the models. Overall, the results in Table B12 indicate that the absence of a contemporaneous within-country association between GAIRI and the five core industrial and technological outcomes is not driven by extreme observations in GDP growth, investment, FDI or trade openness. The stability of both the magnitude and statistical significance of the GAIRI coefficients, therefore, provides additional support for the robustness of the baseline two-way fixed-effects findings.

4.7. Discussion

The central finding of this study is the sharp distinction between contemporaneous within-country changes in government AI readiness and persistent differences in AI-readiness capacity across countries. The two-way fixed-effects models show no statistically significant GAIRI association with any of the five core outcomes, whereas the within-between decomposition identifies positive between-country associations with the manufacturing value-added share ($\beta=0.180$), high-technology exports as a share of manufactured exports ($\beta=0.519$), high-technology exports relative to merchandise exports ($\beta=0.491$), and logged ICT service exports ($\beta=0.168$). This pattern is consistent with the literature conceptualising AI readiness as a multidimensional national capability built upon persistent institutional, technological, data and innovation infrastructures rather than as an input whose economic consequences emerge immediately after annual changes in an index score (Abdullayev et al., 2026; Valaskova et al., 2025). It also complements earlier country-level evidence linking government AI readiness to renewable energy development and digital governance, while extending that literature to manufacturing and export sophistication (Kuzior et al., 2026; Lyeonov et al., 2025). At the same time, the absence of significant short-run within-country effects is compatible with evidence of an AI productivity paradox, according to which complementary investment, organisational adaptation and diffusion processes can delay the translation of technological capacity into measurable economic outcomes (Škare et al., 2025). The present results, therefore, refine rather than contradict the generally positive literature on AI readiness: countries with stronger and more persistent AI-readiness ecosystems tend to exhibit more technologically sophisticated, productive, and export structures, but improvements in readiness over the relatively short 2020–2024 period are not accompanied by immediate structural upgrading within the same economy. Importantly, these between-country relationships are estimated conditional on differences in GDP per capita and the remaining macroeconomic covariates. They therefore suggest that the association between persistent AI-readiness capacity and technological sophistication is not reducible solely to observed income differences, although the high correlation between GAIRI and income requires caution in attributing the coefficients uniquely to AI readiness.

This distinction also helps reconcile the present macro-level results with the predominantly positive evidence obtained at firm and industry levels. Previous research associates digital transformation and AI adoption with firm performance, organisational resilience, supply-chain efficiency and the high-quality development of manufacturing, but these gains are generally conditional on organisational capabilities, managerial adaptation and technological readiness at the enterprise level (Brabete et al., 2026; Susanti et al.,

2026; Wang & Zeng, 2025). Likewise, export-oriented research indicates that internal capabilities and digital transformation can strengthen manufacturing export performance, while enterprise-level readiness frameworks emphasise that technological benefits depend on the interaction of technological, organisational and environmental conditions (Dinh & Tran, 2026; Tashenova et al., 2025; Xu, 2025). Against this background, the insignificant contemporaneous GAIRI coefficients should not be interpreted as evidence that AI-related capabilities are economically irrelevant; rather, they suggest that micro-level efficiency gains and adoption effects do not necessarily aggregate rapidly into changes in national manufacturing or export shares. The study's supplementary tests reinforce this interpretation: neither GDP per capita nor the initial manufacturing base significantly moderates the within-country GAIRI association, while the tentative manufacturing curvature is not confirmed by the formal inverted-U test ($p=0.108$) and disappears after the Benjamini–Hochberg correction ($p_{BH}=0.384$). These results are consistent with a socio-technical interpretation in which AI-driven transformation requires complementary skills, organisational acceptance, investment, and ecosystem conditions, rather than mechanically following from improvements in national readiness indicators (Alhammedi, 2025; Crețu et al., 2024; Mursalov et al., 2023).

The forward-looking sectoral results provide additional evidence that the economic manifestation of AI readiness may be both lagged and sector-specific. The one-year 2020–2021 models offer no robust evidence that initial GAIRI is associated with subsequent changes in medium- and high-technology manufacturing or exports, whereas the 2021–2023 machinery and transport equipment analysis produces the clearest prospective relationship in the study: a one-point higher GAIRI score in 2021 is associated with an approximately 0.505 percentage-point higher machinery share in 2023 ($p=0.0016$), and this result remains statistically significant after false-discovery-rate adjustment ($p_{BH}=0.0047$). This sector-specific pattern accords with research showing that AI and advanced digital technologies are becoming particularly deeply embedded in automotive and smart-manufacturing environments through digital twins, cyber-physical systems, supply-chain intelligence, and changing skill requirements (Kemrichard et al., 2026; Lazaroïu et al., 2024a; Popescu et al., 2025). It is also consistent with the broader Industry 4.0 literature, which emphasises that industrial benefits emerge through sustained technological investment, organisational capabilities and ecosystem adaptation rather than instantaneous adoption (Ślusarczyk, 2025; Tudor et al., 2026). More generally, evidence that entrepreneurial ecosystems, public R&D, and innovation financing can reinforce the commercialisation and diffusion of new technologies provides a plausible explanation for why persistent national AI readiness capacity may matter more than short-term index movements (Mursalov et al., 2023; Sitnicki et al., 2026). Taken together, the findings suggest that government AI readiness is best interpreted as an enabling national capability whose relationship with technological upgrading is visible primarily in persistent cross-country differences and, potentially, in subsequent changes within particular technology-intensive manufacturing segments rather than in immediate economy-wide structural shifts.

5. CONCLUSION

This study examined whether national government AI readiness is associated with the technological structure of production and exports, with particular attention to whether the observed relationships reflect persistent differences in AI-readiness capacity between countries or shorter-term changes occurring within countries. The analysis also assessed whether such associations are more pronounced for technology-intensive activities than for broader industry and manufacturing shares and whether initial AI readiness is prospectively related to subsequent changes in technology-intensive manufacturing structure.

The empirical analysis combined the Oxford Insights Government AI Readiness Index with industrial, technological, trade and macroeconomic indicators from World Bank Open Data. The principal unbalanced panel covers up to 176 countries observed in 2020, 2021, 2023, and 2024, while 2025 is used only for

sensitivity analysis due to changes in the GAIRI methodology. The empirical strategy combined two-way country and year fixed-effects models with a within-between decomposition, quadratic and interaction specifications, baseline-adjusted ANCOVA and change-score models for more disaggregated technological outcomes, and a set of robustness procedures including same-sample estimation, multicollinearity diagnostics, winsorisation, pillar decomposition, within-year standardisation of the 2025 index and Benjamini–Hochberg correction for multiple testing. All calculations were performed in R 4.4.0, with country-clustered standard errors for the panel models and HC3 robust standard errors for the prospective ANCOVA and change-score specifications.

The main findings can be summarised in five results. First, the baseline two-way fixed-effects estimates reveal no statistically significant contemporaneous within-country association between GAIRI and any of the five core outcomes, with GAIRI coefficients of 0.008 for the industry value-added share, 0.022 for the manufacturing value-added share, 0.079 for high-technology exports as a share of manufactured exports, 0.004 for high-technology exports relative to merchandise exports, and 0.001 for logged ICT service exports. Second, conditional on the within- and between-country components of logged GDP per capita and the remaining macroeconomic controls, the within-between decomposition identifies a markedly different cross-country pattern: country-average GAIRI is positively associated with the manufacturing value-added share ($\beta=0.180$), high-technology exports within manufactured exports ($\beta=0.519$), high-technology exports relative to merchandise exports ($\beta=0.491$), and logged ICT service exports ($\beta=0.168$), while the corresponding within-country GAIRI coefficients remain statistically insignificant. Third, manufacturing exhibits only suggestive curvature: the estimated turning point is 57.59 GAIRI points. However, the formal inverted-U test is not significant ($p=0.108$), the joint Wald test is only marginal ($F=2.83$, $p=0.062$), and the quadratic term loses significance after multiple-testing adjustment ($p_{BH}=0.384$). Fourth, the clearest forward-looking result concerns machinery and transport equipment: a one-point higher GAIRI score in 2021 is associated with an approximately 0.505 percentage-point higher machinery share in 2023 in the baseline-adjusted ANCOVA model ($p=0.0016$; $p_{BH}=0.0047$), while the corresponding change-score coefficient is 0.350 ($p=0.021$). However, because this analysis is based on only 76 countries and the fully adjusted specification includes several covariates, the magnitude and precision of these estimates should be interpreted cautiously and regarded as requiring confirmation in larger samples. Fifth, the robustness analyses reinforce this overall interpretation: same-sample estimation, winsorisation of macroeconomic controls, the 2025 sensitivity specification and GAIRI-pillar decomposition do not generate significant contemporaneous GAIRI associations, while the strongest between-country technological relationships remain significant after multiple-testing correction. These estimates, therefore, represent conditional associations with AI readiness rather than unconditional differences associated with countries' levels of economic development.

From a policy perspective, these findings suggest that improvements in national AI readiness should be viewed primarily as part of a long-term capability-building strategy rather than as an instrument expected to generate immediate changes in aggregate industrial structure. Governments should therefore complement AI strategies with sustained investment in digital and data infrastructure, institutional capacity, innovation systems, human capital and the diffusion of AI-related capabilities into productive sectors. The strong between-country relationships indicate that technologically sophisticated manufacturing and export structures tend to coexist with persistent AI-readiness advantages. At the same time, the machinery result suggests that such capabilities may become particularly relevant for specific technology-intensive segments over longer horizons. Policy design should consequently focus not only on raising composite AI-readiness scores but also on connecting public-sector AI capacity, technological ecosystems, and data infrastructure with sector-specific innovation, workforce skills, technology adoption, and export-development programmes. Evaluation frameworks should also recognise potential time lags and assess whether

improvements in AI readiness translate into subsequent changes in sectoral technological composition rather than relying solely on contemporaneous indicators.

Several limitations qualify these conclusions and provide directions for further research. The principal panel contains only four observation waves over 2020–2024 and excludes 2022, limiting the ability to identify gradual or lagged structural adjustments. The methodological redesign of GAIRI in 2025 also prevents its straightforward incorporation into the baseline panel. Data availability is uneven across technologically disaggregated outcomes, particularly for medium- and high-technology manufacturing and machinery indicators, and the prospective machinery analysis is therefore based on a substantially smaller sample of 76 countries. Given the number of regressors in the fully adjusted machinery specifications, this restricted sample limits statistical precision and may increase sensitivity to model specification and influential observations; consequently, the machinery results should be regarded as suggestive prospective evidence requiring confirmation in larger samples. Moreover, the observational research design cannot rule out reverse causality or time-varying omitted factors, so the estimated relationships should not be interpreted causally; the between-country ICT result also warrants particular caution because ICT service exports are measured in absolute monetary terms and may partly reflect persistent country-size differences. Future research should therefore exploit longer and methodologically harmonised GAIRI series, explicitly model lagged responses, normalise digital-export indicators by economic size, and examine AI readiness using more disaggregated sectoral, firm-level and labour-market data. Further work could also investigate how human capital, digital skills, organisational capabilities, and institutional quality interact with national AI readiness to translate technological preparedness into productive transformation, thereby providing a more explicitly human-technology perspective on the mechanisms identified in this study.

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APPENDIX A

Table A1

Descriptive statistics for the analytical variables, 2020–2024

Variable	N	Mean	SD	Min	Median	Max
GAIRI Overall Score	683	46.522	16.682	14.622	42.380	88.160
Industry value added (% GDP)	685	25.901	10.396	2.086	24.385	76.034
Manufacturing value added (% GDP)	662	11.836	6.083	0.752	11.221	34.314
High-tech exports (% manufactured exports)	580	10.777	12.675	0.000	6.305	76.670
High-tech export intensity (% merchandise exports)	584	5.558	9.273	0.000	1.515	54.629
ln(ICT service exports)	627	19.428	3.061	9.018	19.424	26.433
Medium/high-tech manufacturing VA	292	24.527	17.448	0.260	22.264	92.579
Medium/high-tech exports share	292	34.102	23.682	0.037	31.674	81.531
Machinery and transport equipment share	288	17.677	13.218	0.046	15.869	61.477
ln(GDP per capita)	694	8.688	1.394	5.574	8.676	11.616
GDP growth (%)	694	1.875	6.756	−32.909	2.853	43.819
Gross capital formation (% GDP)	617	23.666	7.859	−15.678	23.093	47.921
FDI net inflows (% GDP)	685	3.936	24.749	−296.013	2.277	433.607
Trade openness (% GDP)	620	86.502	54.279	1.995	76.259	402.567

Notes: Descriptive statistics refer to the principal analytical periods of 2020, 2021, 2023, and 2024. Sample sizes vary because of indicator-specific missing observations.

Table A2

Availability of dependent variables by year

Year	Industry VA	Manufacturing VA	High-tech exports share	High-tech export intensity	ln(ICT exports)	MHT manufacturing VA	MHT exports	Machinery share
2020	173	169	155	156	161	146	146	99
2021	173	168	156	157	159	146	146	99
2023	170	164	150	151	156	0	0	76
2024	169	161	119	120	151	0	0	14
2025	150	127	0	0	93	0	0	0

Note: 2025 is shown for completeness but is not included in the principal 2020–2024 descriptive sample. The absence of observations for several high-tech indicators after 2021 reflects World Bank data availability rather than values being set to zero.

Table A3

Availability of GAIRI and control variables by year

Year	GAIRI	GDP per capita	GDP growth	Gross capital formation	FDI	Trade openness
2020	172	174	174	155	172	157
2021	160	174	174	155	172	157
2023	176	173	173	155	171	154
2024	175	173	173	152	170	152
2025	176	169	169	122	95	125

Notes: Trade openness is defined as the sum of exports of goods and services (% of GDP) and imports of goods and services (% of GDP). It is available only when both components are observed.

Table A4

Pairwise correlation matrix for the principal analytical variables

Variable	GAIRI	Industry VA	Manufacturing VA	HT manuf. share	HT export intensity	ln ICT exports	ln GDP pc	GDP growth	Capital	FDI	Trade openness
GAIRI	1.000	0.049	0.254	0.490	0.523	0.805	0.852	0.020	0.064	0.036	0.320
Industry VA	0.049	1.000	0.348	-0.014	-0.014	0.010	0.087	0.131	0.259	-0.053	-0.048
Manufacturing VA	0.254	0.348	1.000	0.229	0.422	0.414	0.112	-0.015	0.135	-0.050	0.075
HT manufactured-export share	0.490	-0.014	0.229	1.000	0.854	0.465	0.399	0.014	0.039	0.098	0.253
HT export intensity	0.523	-0.014	0.422	0.854	1.000	0.527	0.394	0.003	0.061	0.156	0.339
ln ICT exports	0.805	0.010	0.414	0.465	0.527	1.000	0.625	-0.009	-0.046	-0.046	0.165
ln GDP per capita	0.852	0.087	0.112	0.399	0.394	0.625	1.000	-0.014	0.025	0.043	0.425
GDP growth	0.020	0.131	-0.015	0.014	0.003	-0.009	-0.014	1.000	0.192	0.092	0.095
Gross capital formation	0.064	0.259	0.135	0.039	0.061	-0.046	0.025	0.192	1.000	0.013	-0.021
FDI	0.036	-0.053	-0.050	0.098	0.156	-0.046	0.043	0.092	0.013	1.000	0.176
Trade openness	0.320	-0.048	0.075	0.253	0.339	0.165	0.425	0.095	-0.021	0.176	1.000

Notes: Pearson correlations are calculated using pairwise complete observations. Correlations are descriptive and should not be interpreted as causal effects.

Table A5

Annual distribution and availability of the GAIRI Overall Score

Year	Potential N	Available N	Missing N	Mean	SD	Min	Median	Max
2020	176	172	4	44.2	15.9	19.1	39.6	85.5
2021	176	160	16	47.4	16.7	17.9	44.1	88.2
2023	176	176	0	46.0	16.7	18.1	42.0	84.8
2024	176	175	1	48.4	17.2	14.6	43.9	87.0
Total/overall	704	683	21	46.52	16.68	14.62	42.38	88.16

Notes: The overall descriptive statistics in the final row are calculated over all available country-year GAIRI observations and therefore are not simple averages of the four annual statistics.

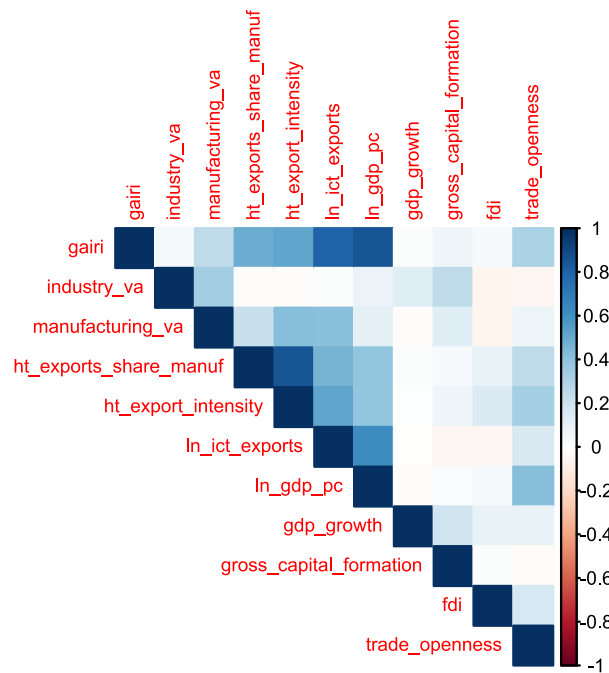


Figure A1. Pairwise correlations among GAIRI, industrial and technological outcomes, and macroeconomic controls, 2020–2024

Notes: Colour intensity represents the magnitude and sign of Pearson pairwise correlations. Correlations use pairwise complete observations.

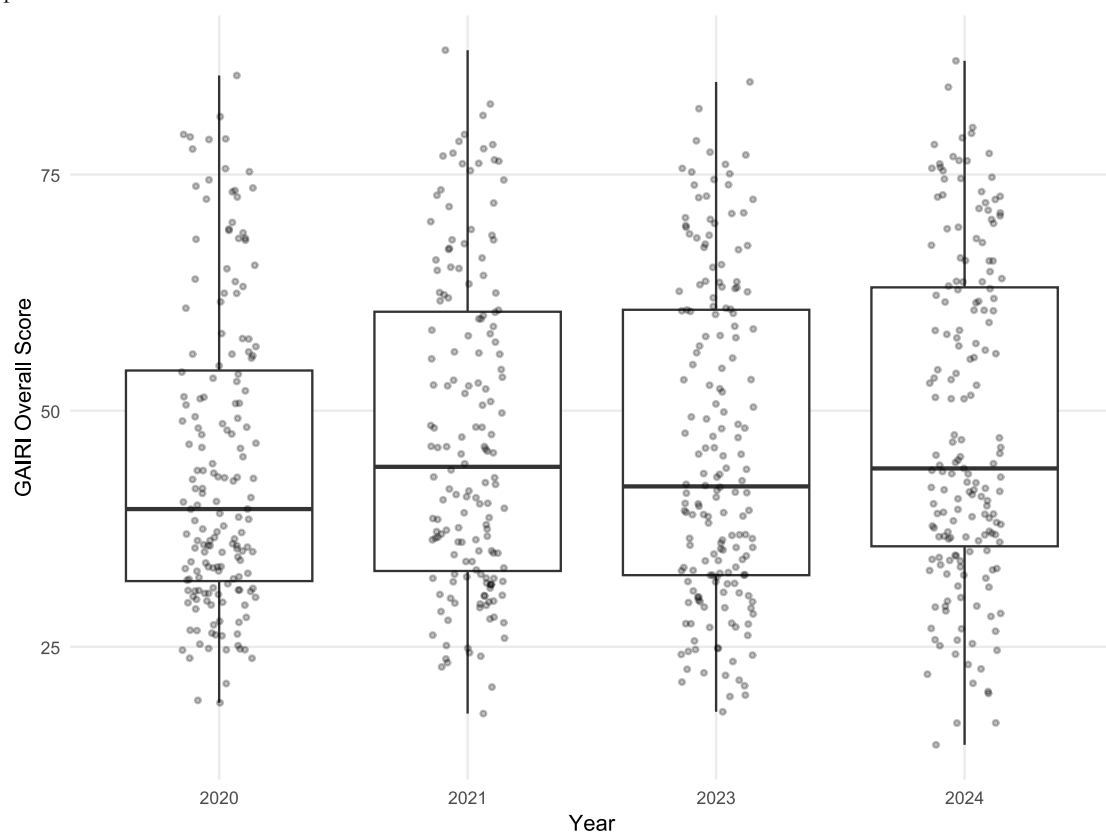


Figure A2. Distribution of the GAIRI Overall Score across countries by year, 2020–2024

Notes: Boxes represent the interquartile range, horizontal lines denote medians, whiskers show the conventional boxplot range, and grey points represent individual country observations. The year 2022 is absent from the analytical dataset.

APPENDIX B

Table B1

Non-linear association between GAIRI and industrial and technological outcomes

Variable/diagnostic	Industry VA	Manufacturing VA	High-tech / manufactured exports	High-tech / merchandise exports	ICT service exports
GAIRI, centred	0.0065 (0.0333)	0.0246 (0.0161)	0.0991 (0.0787)	0.0060 (0.0330)	0.0007 (0.0094)
GAIRI ²	0.0006 (0.0012)	−0.0011 [†] (0.0006)	−0.0041 (0.0041)	−0.0003 (0.0015)	0.0001 (0.0003)
GAIRI range in estimation sample	—	19.74–88.16	—	—	—
Turning point	—	57.59	—	—	—
95% CI for turning point	—	[38.46, 76.71]	—	—	—
Slope at lower bound	—	0.084	—	—	—
One-sided (p), lower slope (>0)	—	0.012	—	—	—
Slope at upper bound	—	−0.068	—	—	—
One-sided (p), upper slope (<0)	—	0.108	—	—	—
Formal inverted-U test, (p)	—	0.108	—	—	—
Joint Wald (F)	—	2.83	—	—	—
Joint Wald (p)	—	0.062	—	—	—
BH-adjusted (p) for GAIRI ²	—	0.384	—	—	—
Observations	588	571	509	513	553
R ²	0.969	0.984	0.923	0.967	0.975
Within R ²	0.010	0.042	0.053	0.061	0.025

Notes: GAIRI is mean-centred before constructing the quadratic term. For the manufacturing specification, the turning point is calculated from the estimated linear and quadratic coefficients and transformed back to the original GAIRI scale. Its confidence interval is obtained using the delta method. The formal inverted-U test evaluates whether the slope is significantly positive at the lower bound and significantly negative at the upper bound of GAIRI observed in the manufacturing estimation sample. The reported value corresponds to an intersection-union endpoint-slope test based on country-clustered standard errors. The joint Wald test evaluates the null that the linear and quadratic GAIRI terms are jointly zero. Significance codes: [†] p<0.10, * p<0.05, ** p<0.01.

Table B2

Economic absorptive capacity as a moderator of the association between GAIRI and industrial and technological outcomes.

Variable	Industry VA	Manufacturing VA	High-tech / manufactured exports	High-tech/merchandise exports	ICT service exports
GAIRI, centred	0.0084 (0.0328)	0.0213 (0.0165)	0.0781 (0.0742)	0.0014 (0.0300)	0.0011 (0.0087)
ln GDP per capita, centred	-2.289 (5.664)	-3.241* (1.519)	11.600† (6.777)	4.642 (3.496)	1.606* (0.649)
GAIRI × ln GDP per capita	0.0123 (0.0231)	-0.0107 (0.0108)	0.0063 (0.0866)	0.0336 (0.0227)	0.0002 (0.0059)
Observations	588	571	509	513	553
R ²	0.969	0.984	0.923	0.967	0.975
Within R ²	0.010	0.033	0.046	0.065	0.025
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Country-clustered SE	Yes	Yes	Yes	Yes	Yes

Notes: Coefficients are reported with country-clustered standard errors in parentheses. GAIRI and logged GDP per capita are mean-centred before their interaction is constructed. All models additionally control for GDP growth, gross capital formation, FDI and trade openness. Because logged GDP per capita is mean-centred, the coefficient on centred GAIRI represents the conditional GAIRI association at the sample mean of logged GDP per capita; the interaction coefficient indicates how this association changes as the moderator departs from its mean. Significance codes: † p<0.10, * p<0.05, ** p<0.01.

Table B3

Initial manufacturing capacity as a moderator of the GAIRI–high-technology export relationship

Variable	High-tech/merchandise exports
GAIRI, centred	0.0128 (0.0331)
ln GDP per capita	5.4766 (3.6182)
GDP growth	-0.0902† (0.0526)
Gross capital formation	-0.0925 (0.0751)
FDI	-0.0149† (0.0082)
Trade openness	0.0129 (0.0159)
GAIRI × manufacturing base (2020)	-0.0079 (0.0072)
Observations	509
Adjusted R ²	0.953
Within R ²	0.067
RMSE	1.770
Country fixed effects	Yes
Year fixed effects	Yes
Country-clustered SE	Yes

Notes: The manufacturing base is defined as manufacturing value added (% of GDP) in 2020 and is mean-centred before constructing the interaction with centred GAIRI. Its level is time-invariant and therefore absorbed by the country fixed effects. Accordingly, the coefficient on centred GAIRI represents its conditional association when the 2020 manufacturing value-added share is at its sample mean. Significance codes: † p<0.10, * p<0.05, ** p<0.01.

Table B4

Marginal effect of GAIRI on high-technology export intensity

Marginal effect	Estimate	SE	(z)	(p)-value	95% CI
GAIRI (dY/dX)	0.00083	0.0301	0.028	0.978	[-0.0582, 0.0599]

Notes: The reported quantity is the average marginal effect of centred GAIRI on high-technology exports relative to total merchandise exports. It is obtained by evaluating the conditional marginal effect of GAIRI at each observed value of the 2020 manufacturing-base moderator and averaging these effects across the estimation sample; it is therefore not evaluated at a single moderator value. The 95% confidence interval includes zero by a wide margin, indicating no statistically detectable average marginal association.

Table B5

Baseline-adjusted ANCOVA models for medium- and high-technology manufacturing and exports, 2020–2021

Variable	MHT manufacturing VA share, 2021	MHT exports share, 2021
GAIRI, 2020	−0.011 (0.046)	0.107† (0.063)
Dependent variable, 2020	0.967*** (0.028)	0.945*** (0.023)
ln GDP per capita, 2020	0.373 (0.487)	−1.435† (0.822)
GDP growth, 2020	0.010 (0.032)	0.009 (0.055)
Gross capital formation, 2020	0.057 (0.041)	−0.017 (0.047)
FDI, 2020	0.004 (0.006)	0.003 (0.018)
Trade openness, 2020	−0.002 (0.005)	0.010 (0.008)
Observations	130	130
Robust standard errors	HC3	HC3

Notes: Coefficients are reported with HC3 heteroskedasticity-robust standard errors in parentheses. The dependent variable baseline term refers to medium- and high-technology manufacturing value added in 2020 in column 1 and the medium- and high-technology export share in 2020 in column 2. Significance codes: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table B6

Change-score robustness models for medium- and high-technology manufacturing and exports, 2020–2021

Variable	Change in MHT manufacturing VA share	Change in MHT exports share
GAIRI, 2020	−0.038 (0.031)	0.060 (0.052)
ln GDP per capita, 2020	0.381 (0.462)	−1.502† (0.856)
GDP growth, 2020	0.011 (0.028)	−0.017 (0.058)
Gross capital formation, 2020	0.053 (0.040)	−0.012 (0.049)
FDI, 2020	0.004 (0.006)	0.001 (0.021)
Trade openness, 2020	−0.002 (0.005)	0.007 (0.008)
Observations	130	130
Robust standard errors	HC3	HC3

Notes: The dependent variables are calculated as the 2021 value minus the corresponding 2020 value. Coefficients are reported with HC3 heteroskedasticity-robust standard errors in parentheses. Significance codes: † p<0.10, * p<0.05, ** p<0.01.

Table B7

Same-sample robustness of the GAIRI coefficients across the core outcomes

Outcome	GAIRI + country/year FE	GAIRI + controls + country/year FE	Observations	Within R ² , simple	Within R ² , controlled
Industry value-added share	0.003 (0.035)	0.008 (0.033)	588	0.000	0.010
Manufacturing value- added share	0.013 (0.017)	0.022 (0.016)	571	0.002	0.030
High-tech / manufactured exports	0.081 (0.073)	0.079 (0.074)	509	0.003	0.046
High- tech/merchandise exports	0.004 (0.030)	0.005 (0.030)	513	0.000	0.061
ICT service exports	0.003 (0.008)	0.001 (0.009)	553	0.000	0.025

Notes: The table reports the GAIRI coefficient from two-way fixed-effects models estimated on identical outcome-specific samples. The first specification includes GAIRI together with country and year fixed effects; the second additionally controls for logged GDP per capita, GDP growth, gross capital formation, FDI net inflows and trade openness. Country-clustered standard errors are reported in parentheses. For each outcome, the simple and controlled specifications use the same observations. None of the GAIRI coefficients is statistically significant at conventional levels.

Table B8

Multicollinearity diagnostics for the core manufacturing specification

Variable	VIF	Tolerance
GAIRI Overall Score	4.365	0.229
ln GDP per capita	4.881	0.205
GDP growth	1.064	0.940
Gross capital formation	1.031	0.970
FDI	1.042	0.960
Trade openness	1.312	0.762

Notes: Variance inflation factors (VIFs) and tolerance values are reported as complementary multicollinearity diagnostics and are not evaluated against a strict universal cut-off. The comparatively higher VIF values and lower tolerance values for GAIRI and logged GDP per capita indicate moderate collinearity, consistent with their strong bivariate association. The remaining regressors display substantially lower VIF values and higher tolerance values. The diagnostics indicate moderate multicollinearity between GAIRI and economic development, but no evidence of severe multicollinearity in the model.

Table B9

Sensitivity to inclusion of 2025 using within-year standardised GAIRI

Variable	Industry VA	Manufacturing VA
Standardised GAIRI	0.129 (0.413)	0.336 (0.232)
Observations	654	633
R ²	0.970	0.984
Within R ²	0.008	0.024
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Country-clustered SE	Yes	Yes

Notes: GAIRI is standardised separately within each year prior to estimation. Consequently, the coefficient on standardised GAIRI represents the conditional association corresponding to a one-standard-deviation difference in GAIRI relative to the distribution observed within the respective year, rather than to a one-point difference on the original index scale. This transformation addresses differences in annual scale and distribution but does not remove methodological changes in the construction of the 2025 GAIRI index. The 2025 specification is therefore treated as a sensitivity analysis and is not part of the principal 2020–2024 analytical sample.

Table B10

GAIRI pillar decomposition for high-technology export intensity

Variable	Government	Technology Sector	Data & Infrastructure
Government pillar	0.011 (0.015)	–	–
Technology Sector pillar	–	–0.070 (0.067)	–
Data & Infrastructure pillar	–	–	0.002 (0.019)
ln GDP per capita	4.800 (3.501)	5.312 (3.649)	4.900 (3.496)
GDP growth	–0.085 (0.051)	–0.090† (0.052)	–0.085 (0.052)
Gross capital formation	–0.090 (0.072)	–0.088 (0.071)	–0.090 (0.073)
FDI	–0.015† (0.009)	–0.014† (0.009)	–0.014† (0.009)
Trade openness	0.014 (0.016)	0.014 (0.016)	0.013 (0.016)
Observations	513	513	513
R ²	0.967	0.967	0.967
Within R ²	0.062	0.066	0.061
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes: Each GAIRI pillar is entered separately. All models include the same macroeconomic controls, country fixed effects and year fixed effects. Country-clustered standard errors are reported in parentheses. Significance codes: † p<0.10, * p<0.05, ** p<0.01.

Table B11

Multiple-testing robustness of the GAIRI-related estimates

Test family	Outcome	Focal test	Raw (p)	BH-adjusted (p)
Core TWFE	Industry VA	GAIRI	0.8139	0.8999
	Manufacturing VA	GAIRI	0.1849	0.7190
	High-tech / manufactured exports	GAIRI	0.2876	0.7190
	High-tech/merchandise exports	GAIRI	0.8823	0.8999
	ICT service exports	GAIRI	0.8999	0.8999
Within-between decomposition	Industry VA	GAIRI_B	0.3574	0.3574
	Manufacturing VA	GAIRI_B	0.0119	0.0149
	High-tech / manufactured exports	GAIRI_B	0.0004	0.0007
	High-tech/merchandise exports	GAIRI_B	<0.0001	<0.0001
	ICT service exports	GAIRI_B	<0.0001	<0.0001
Non-linearity	Industry VA	GAIRI ²	0.6090	0.8346
	Manufacturing VA	GAIRI ²	0.0768	0.3840
	High-tech / manufactured exports	GAIRI ²	0.3157	0.7893
	High-tech/merchandise exports	GAIRI ²	0.8346	0.8346
	ICT service exports	GAIRI ²	0.6957	0.8346
Heterogeneity	Industry VA	GAIRI × ln GDP _{pc}	0.5958	0.9742
	Manufacturing VA	GAIRI × ln GDP _{pc}	0.3202	0.8006

	High-tech / manufactured exports	$\text{GAIRI} \times \ln \text{GDP}_{\text{pc}}$	0.9418	0.9742
	High-tech/merchandise exports	$\text{GAIRI} \times \ln \text{GDP}_{\text{pc}}$	0.1400	0.6998
	ICT service exports	$\text{GAIRI} \times \ln \text{GDP}_{\text{pc}}$	0.9742	0.9742
Prospective ANCOVA	MHT manufacturing VA, 2021	Initial GAIRI	0.8048	0.8048
	MHT exports share, 2021	Initial GAIRI	0.0926	0.1389
	Machinery share, 2023	Initial GAIRI	0.0016	0.0047
Change-score robustness	Change in MHT manufacturing VA	Initial GAIRI	0.2143	0.2527
	Change in MHT exports	Initial GAIRI	0.2527	0.2527
	Change in machinery share	Initial GAIRI	0.0214	0.0641†

Notes: Benjamini–Hochberg adjustments control the false discovery rate within substantively defined families of GAIRI-related tests. Adjustments are therefore conducted separately for the core TWFE, within–between, non-linear, heterogeneity, prospective ANCOVA and change-score families. The macroeconomic control coefficients are not included in the correction. GAIRI_B denotes the between-country component of GAIRI in the within–between decomposition. MHT denotes medium- and high-technology. Bold values indicate BH-adjusted $p < 0.05$; † indicates BH-adjusted $p < 0.10$. Values reported as < 0.0001 were rounded to 0.0000 in the underlying output and should not be presented as exactly zero.

Table B12

Robustness of the GAIRI coefficients to winsorisation of macroeconomic controls

Outcome	Baseline controls	Winsorised controls	Observations	Within R ² , baseline	Within R ² , winsorised
Industry value-added share	0.0077 (0.0328)	0.0071 (0.0330)	588	0.010	0.009
Manufacturing value-added share	0.0219 (0.0164)	0.0218 (0.0165)	571	0.030	0.035
High-tech / manufactured exports	0.0787 (0.0737)	0.0781 (0.0754)	509	0.046	0.058
High-tech/merchandise exports	0.0045 (0.0302)	0.0036 (0.0308)	513	0.061	0.052
ICT service exports	0.0011 (0.0087)	0.0013 (0.0087)	553	0.025	0.023

Notes: Coefficients are reported with country-clustered standard errors in parentheses. The baseline specifications include logged GDP per capita, GDP growth, gross capital formation, FDI and trade openness. In the winsorised specifications, GDP growth, gross capital formation, FDI and trade openness are winsorised at the 1st and 99th percentiles within each outcome-specific estimation sample; GAIRI, logged GDP per capita, and the dependent variables are not winsorised. Baseline and winsorised specifications use identical observations and include country and year fixed effects. None of the GAIRI coefficients is statistically significant at conventional levels.