Supply chain readiness and export performance in Africa: evidence from interpretable machine learning

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Abstract

Purpose – This study examines whether a multidimensional supply-chain readiness system predicts export performance across African economies and whether the relationships persist when export performance is measured through aggregate value, extensive product breadth and intensive product depth rather than exports relative to GDP.

Design/methodology/approach – The analysis begins with a 54-country, 1985–2024 country-year grid while retaining original missing observations. Export intensity is retained as a benchmark. Additional outcomes comprise log merchandise export value, the number of exported HS-6 products and log export value per HS-6 product. Ridge, Random Forest, Extra Trees and Gradient Boosting are assessed with temporal, random, country-group and rolling validation.

Findings – Extra Trees remains the strongest benchmark model (R-squared = 0.651). Predictive performance is also high for log merchandise exports (R-squared = 0.926), exported HS-6 product breadth (R-squared = 0.891) and log exports per HS-6 product (R-squared = 0.824). The complete-case benchmark, estimated without numerical imputation, records R-squared = 0.737. Country demeaning lowers R-squared to 0.242 for export intensity and 0.283 for log merchandise exports, confirming that pooled machine learning captures substantial between-country structure. Within-country importance nevertheless retains industry employment for export intensity and manufacturing value added for merchandise export value as leading readiness signals.

Originality/value – The study combines interpretable machine learning with alternative export-performance margins, explicit missing-data sensitivity and a pooled-versus-within-country bridge. The results distinguish predictive cross-country structure from within-country change and provide a more cautious basis for connecting supply-chain readiness to export breadth and depth.

Keywords Export performance, Export intensity, Extensive margin, Intensive margin, Supply-chain readiness, Interpretable machine learning

Paper type Research article

1. Introduction

Export performance remains central to African development because it connects domestic production to foreign demand, scale economies, learning and structural transformation. Trade

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theory links export outcomes to technology, factor costs, firm productivity, market access and trade costs (Melitz and Redding, 2021; Larch and Yotov, 2024; Antràs and Chor, 2022). These channels matter in Africa, where uneven infrastructure, fragmented logistics systems, narrow production bases and uneven digital connectivity constrain cross-border participation (Kuteyi and Winkler, 2022).

A supply-chain readiness perspective explains why export outcomes differ across African subregions. Exporting requires comparative advantage, but it also requires supplier coordination, reliable electricity, information systems, finance, transport connectivity and dependable border processes. Supply-chain research links performance to coordination, resilience, information flows and logistics reliability (Govindan *et al.*, 2022; Jha *et al.*, 2022; Castillo, 2023), while African trade evidence identifies infrastructure gaps and border delays as persistent constraints (Tandrayen-Ragoobur *et al.*, 2023; Olyanga *et al.*, 2022; Wassie *et al.*, 2025).

The determinant set is broadened beyond general macroeconomic proxies. Vogel (2025) shows that African export diversification reflects structural conditions, tariffs, regional integration, institutions, services, resource dependence, finance, foreign investment and exchange-rate stability. Consistent with that evidence, the present framework incorporates digital readiness, energy access and efficiency, manufacturing capacity, industrial employment, private credit, production-cost conditions, trade facilitation, transport connectivity, export capacity and direct logistics measures. GDP per capita, population, density, services, lagged FDI, resource rents and geographic characteristics are treated as controls rather than direct readiness measures.

The research question is therefore whether supply-chain readiness predicts export performance across African economies, whether those predictive relationships remain stable in later periods, and how strongly they persist under alternative aggregate, extensive-margin and intensive-margin outcomes. Exports of goods and services as a percentage of GDP is retained only as the export-intensity benchmark. Trade (% of GDP), imports (% of GDP) and current account balance remain excluded from the main specifications because they are mechanically or substantively close to that benchmark and may create accounting overlap or trade-openness endogeneity.

The contribution is in fivefold. Firstly, the study defines supply-chain readiness as an antecedent national capacity and distinguishes it from realised logistics performance, border-process facilitation, disruption resilience and foreign-market preparedness. Second, it separates direct readiness indicators from structural controls and outcome-related exclusions. Third, it uses temporal, country-group and rolling validation rather than relying on a random split alone. Fourth, it tests export performance through aggregate value, product breadth and product depth to reduce dependence on the exports-to-GDP ratio. Fifth, it combines SHAP, permutation importance, complete-case sensitivity, country-and-year fixed effects and country-demeaned machine learning so that pooled structural prediction is not mistaken for within-country progress or causal policy impact.

2. Literature review and analytical positioning

2.1 Supply-chain readiness and related concepts

Supply-chain readiness is defined here as the ex-ante capacity of an economy to coordinate production inputs, infrastructure, information, finance, border processes and delivery systems before export transactions occur. It is broader than logistics performance, which reflects realised customs efficiency, infrastructure quality, shipment arrangement, logistics competence, tracking and timeliness (World Bank, 2023). It is also broader than trade facilitation, which concentrates on the time, cost, documentation and predictability of border procedures (Wassie *et al.*, 2025).

Supply-chain resilience concerns the ability of production and logistics networks to absorb, adapt to and recover from disruption (Ivanov and Dolgui, 2020; Castillo, 2023), whereas export readiness commonly concerns preparedness to enter and serve foreign markets. The present construct treats these concepts as related but non-equivalent: readiness represents the underlying capacity set; logistics performance and border outcomes represent observable manifestations; resilience concerns response under disruption; and export readiness is closer to firm- or product-level market-entry preparedness.

2.2 Theoretical foundation

Two complementary theoretical perspectives provide the foundation for the readiness construct. Heterogeneous-firm trade theory emphasises productivity and the fixed and variable costs of entering and serving foreign markets; at the national level, electricity, finance, productive capacity, digital connectivity and transport conditions shape the environment in which firms absorb those costs and scale export activity (Melitz and Redding, 2021; Larch and Yotov, 2024). A transaction-cost and supply-chain capability perspective adds the coordination mechanism: reliable information, supplier linkages, logistics competence and predictable border processes reduce search, contracting, delay and delivery frictions across fragmented production networks (Antràs and Chor, 2022; Govindan *et al.*, 2022; Jha *et al.*, 2022). These mechanisms imply effects on both margins of trade. Readiness can broaden the set of viable product-market combinations and can deepen established export relationships by lowering recurring coordination and delivery costs. The alternative outcome analysis therefore treats aggregate value, HS-6 product breadth and average value per HS-6 product as distinct empirical manifestations of export capacity.

2.3 Readiness dimensions and African export performance

Digital connectivity lowers search, communication and coordination costs. Internet access and mobile connectivity can support buyer discovery, transaction records, shipment coordination and regional market participation (Kere and Zongo, 2023; Xing *et al.*, 2026). Energy access and lower power losses support production continuity, cold storage, digital systems and service delivery. Productive and financial readiness is reflected in manufacturing value added, industrial employment, capital formation and private-sector credit, consistent with evidence that productive capabilities shape African export performance (Avenyo *et al.*, 2021).

Trade facilitation and transport connectivity are added as separate readiness dimensions. Border and documentary compliance time and cost, export lead time, tariffs, air freight and liner-shipping connectivity capture frictions that are not represented by broad income or sectoral shares. Direct logistics measures cover customs, infrastructure, international shipments, logistics competence, tracking and timeliness. Firm-level and Africa-focused evidence links these conditions to export outcomes and international competitiveness (Bugarčić *et al.*, 2024; Wassie *et al.*, 2025).

Controls are retained to represent structural heterogeneity rather than readiness interventions. GDP per capita captures development level; population and density capture market size and spatial concentration; services value added captures economic structure; lagged FDI captures external capital; resource rents capture commodity dependence; and subregion, landlocked and island status capture geography. Vogel (2025) reinforces the need to account for such contextual differences when analysing African export outcomes.

2.4 Why interpretable machine learning is used

Conventional panel models are useful for estimating average conditional associations under a specified functional form. Machine learning serves a different purpose: it can accommodate nonlinear thresholds, interactions, missingness indicators and heterogeneous predictor combinations while evaluating out-of-sample accuracy (Masini *et al.*, 2023; Goulet Coulombe, 2024). The approach is therefore selected for prediction and pattern discovery, not causal identification. A country-and-year fixed-effects model with lagged predictors is retained as a conventional benchmark so that predictive rankings can be compared with within-country associations.

Interpretability is treated as part of the design rather than an afterthought. Permutation importance evaluates loss of holdout accuracy after a feature is disrupted; SHAP values show the direction and size of local predictive contributions; dependence plots reveal nonlinear patterns and interaction colouring; subregional errors expose geographic heterogeneity; and rolling validation evaluates stability across successive later-period windows. (See Supplementary Table S5 and Supplementary Figures S3, S4, S5 and S6).

3. Data and methods

3.1 Data scope, outcome and variable treatment

The data structure is a 54-country by 40-year grid covering 1985–2024, equivalent to 2,160 possible country-years. The grid is not treated as a complete balanced analytical sample. Original missing observations are retained and reported. The export-intensity benchmark is observed for 1,735 country-years. The core annual specification uses 1,711 observations from 51 economies; the extended specification uses 1,711 observations from 51 economies; and the direct-logistics specification uses 467 observations from 51 economies over 2007–2022. The alternative outcomes add 1,962 observations for log merchandise export value across 54 economies during 1988–2024 and 1,185 observations for HS-6 product breadth and product-depth measures across 49 economies during 1990–2023. (See Table 1). (See Supplementary Table S3 and Supplementary Figure S8).

Export intensity, measured as exports of goods and services as a percentage of GDP, is retained as the benchmark rather than treated as a complete measure of export performance. To reduce structural scale bias, three estimable alternatives are analysed: the natural logarithm of total merchandise exports in current US dollars, the number of HS-6 products exported in a reporter-year, and the natural logarithm of merchandise export value per exported HS-6 product. The intended destination-partner breadth and per-partner depth outcomes did not yield a usable country-year series in the retrieved WITS indicators and are reported as unavailable rather than filled by imputation. The product-based extensive and intensive margins therefore provide the estimable decomposition of breadth and depth.

Table 2 separates direct readiness measures from controls and explicitly records the three outcome-related exclusions. This treatment prevents the high importance previously attached to imports from being interpreted as evidence of readiness when it may largely reflect general trade openness. (See Supplementary Table S1, Supplementary Table S4 and Supplementary Figure S2).

The benchmark pipelines retain numerical median imputation learned from each training sample, together with missingness indicators, while categorical imputation and one-hot encoding are also learned within training data. The sensitivity design directly tests whether this treatment drives the findings. For the alternative-outcome and pooled-versus-within-country

Table 1. Analytical samples and missing-data treatment

Analytical scope	Countries	Rows	Period	Treatment
Target country-year grid	54	2,160	1985–2024	Missing observations retained
Observed export-performance values	54	1,735	1985–2024	Outcome available
Core annual specification	51	1,711	1985–2024	Temporal cutoff: 2017
Extended readiness specification	51	1,711	1985–2024	Temporal cutoff: 2017
Direct logistics specification	51	467	2007–2022	Temporal cutoff: 2018
Aggregate export-value outcome	54	1,962	1988–2024	Temporal cutoff: 2017
HS-6 product breadth/depth outcomes	49	1,185	1990–2023	Temporal cutoff: 2017

Source(s): Computations from the study dataset (2026)

Table 2. Variable framework and modelling treatment

Role	Dimension	Indicators	Treatment
Outcome	Export performance	Exports of goods and services (% of GDP)	Dependent variable; described as export intensity
Core readiness	Digital, energy, productive and financial capacity	Internet use; mobile subscriptions; electricity access; manufacturing value added; industry employment; private-sector credit; inflation	Primary annual specification
Extended readiness	Trade facilitation, transport, production cost and export capacity	Power losses; tariffs; air freight; shipping connectivity; lead time; border and documentary time/cost; documents; REER; manufactured and high-technology exports; secure servers	Robustness specification
Direct logistics	Operational logistics quality	Customs; infrastructure; international shipments; logistics competence; tracking; timeliness	Sparse-year robustness specification
Controls	Development, structure and geography	Log GDP per capita; log population; density; services; lagged FDI; resource rents; subregion; landlocked; island	Not interpreted as direct readiness levers
Excluded	Outcome-related aggregates	Trade (% of GDP); imports (% of GDP); current account balance	Removed from the main specifications
Outcome robustness	Aggregate value; extensive and intensive product margins	Log merchandise exports; exported HS-6 products; log exports per HS-6 product	Alternative outcome analysis

Source(s): Computations from the study dataset (2026)

analyses, predictors with more than 50% missingness in the relevant benchmark sample are excluded; the retained variables have missingness between 0% and 22.02%, while gross fixed capital formation is excluded because it has no usable observations. A separate complete-case Extra Trees model uses no numerical imputation. Sparse trade-facilitation and logistics variables remain confined to their period-specific robustness specifications. (See Supplementary Tables S2 and S10).

3.2 Predictive and conventional estimation strategy

The supervised stage estimates a mean benchmark, ridge regression, Random Forest, Extra Trees and Gradient Boosting. The primary export-intensity test trains before 2017 and evaluates 2017 onward; the direct-logistics specification uses a 2018 cutoff because its measures are available only in selected years. The same 2017 temporal design is applied to log merchandise export value, exported HS-6 product breadth and log export value per HS-6 product. Random observation splitting remains a secondary comparison, country-group cross-validation keeps countries separated across folds, and four rolling three-year windows assess later-period stability. (See Supplementary Table S5 and Supplementary Figures S3 and S4).

The core specification includes annual digital, energy, productive and financial indicators. The extended specification adds energy efficiency, tariffs, air freight, liner-shipping connectivity, export lead time, border and documentary compliance, the number of export documents, the real effective exchange rate, manufactured and high-technology exports and secure internet servers. The direct-logistics specification uses the six Logistics Performance Index components together with available trade-facilitation and shipping measures.

Model performance is evaluated with mean absolute error, root mean squared error and *R*-squared. Permutation importance and SHAP are calculated for the strongest temporal tree model, and alternative-outcome permutation importance is used to compare structural controls with readiness signals. Two additional diagnostics bridge pooled prediction and panel inference. First, a complete-case temporal Extra Trees model removes numerical imputation. Second, country means are estimated from the training period and both outcomes and predictors are expressed as deviations from those training-period means before temporal testing. This country-demeaned machine-learning design measures within-country predictive variation without allowing time-invariant level differences to dominate. Country-level PCA and K-means clustering remain based on averages of readiness predictors only, while the fixed-effects benchmark includes one-year-lagged core predictors, country and year effects, and country-clustered standard errors. (See Supplementary Tables S6a, S6b, S7, S11, S12 and S13; Supplementary Figures S6, S7, S11, S12 and S13).

Figure 1 shows the distinction between readiness dimensions, controls, predictive assessment and the export-performance outcome. The excluded aggregates are stated below the framework to make the screening decision auditable.

3.3 Interpretation limits

All results are interpreted as predictive associations. Permutation and SHAP values indicate contributions to prediction, not the effect of a feasible policy intervention. Pooled machine-learning importance can reflect persistent differences across countries as well as changes over time, so the country-demeaned analysis is used to quantify the within-country component directly. The fixed-effects estimates and country-demeaned machine-learning results remain associational because neither lagging predictors nor removing country and year averages establishes exogenous variation.

4. Results

4.1 Subregional structure and data coverage

Observed export performance varies across subregions and is not available for every possible country-year. Southern Africa has the highest mean export intensity in the observed sample, while West Africa has the largest number of observed outcomes. The unequal coverage

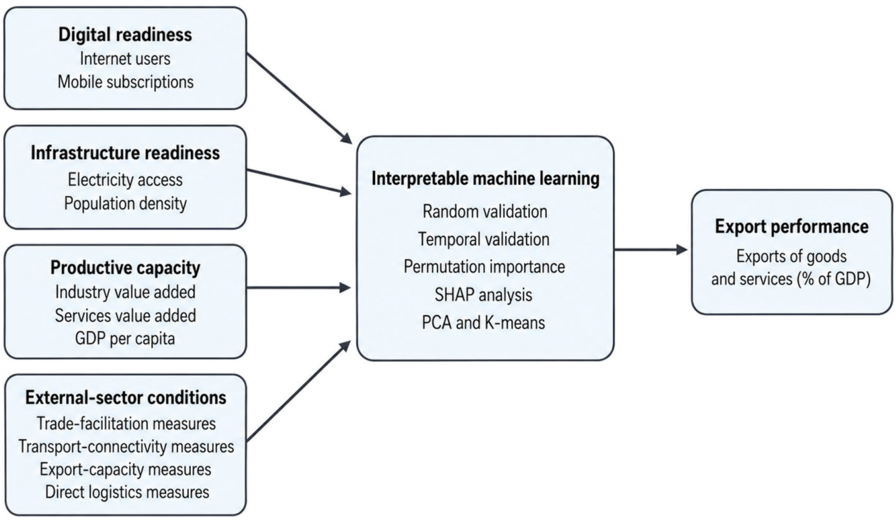

Figure 1. Multidimensional supply-chain readiness and export-performance framework. Source: Authors' own construct (2026)

reinforces the decision to report sample sizes and retain a missingness audit rather than constructing an artificial complete panel. (See Table 3).

Figure 2 shows persistent subregional differences and substantial year-to-year variation. The temporal structure supports the use of later-period validation rather than a single randomly mixed test sample. (See Supplementary Figure S1).

4.2 Core model performance

Extra Trees records the strongest core temporal performance, with MAE of 8.496, RMSE of 14.149 and *R*-squared of 0.651. Its random-split *R*-squared is 0.949, demonstrating that randomly mixing years and countries produce a much more optimistic assessment. The temporal result is therefore retained as the primary estimate of predictive performance. (See Table 4). (See Supplementary Figures S3 and S4).

Figure 3 shows that the preferred model captures the central range of export intensity more accurately than extreme observations. This pattern explains why the temporal *R*-squared remains useful but materially lower than the random-split result.

Table 3. Subregional distribution of observed export performance

Subregion	Countries	Target grid rows	Observed outcome	Mean export performance
Central Africa	9	360	291	36.27
East Africa	18	720	501	28.54
North Africa	6	240	235	28.47
Southern Africa	5	200	150	40.88
West Africa	16	640	558	23.09

Source(s): Computations from the study dataset (2026)

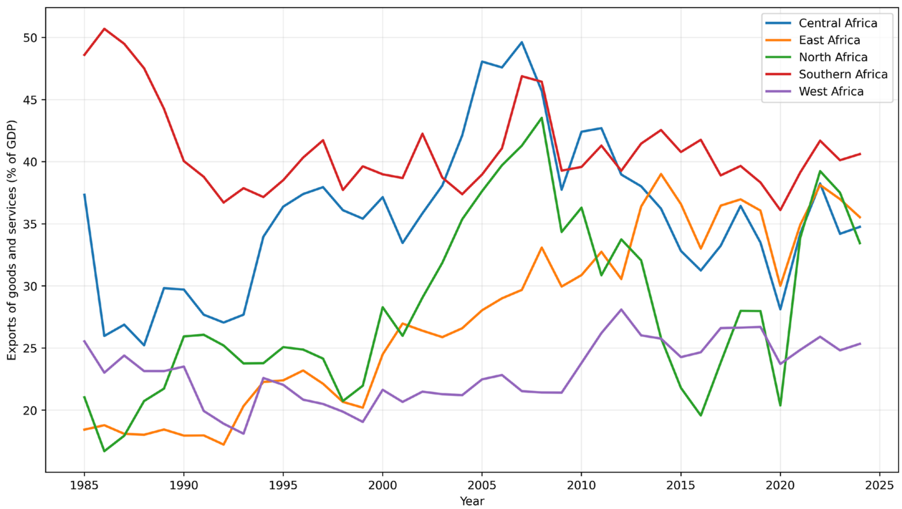

Figure 2. Export-performance trends by African subregion. Source: Computations from the study dataset (2026)

Table 4. Core model performance under temporal and random validation

Validation	Model	Training N	Test N	MAE	RMSE	*R*-squared
Temporal holdout	Extra Trees	1,322	389	8.496	14.149	0.651
Temporal holdout	Random Forest	1,322	389	10.171	18.110	0.429
Temporal holdout	Gradient Boosting	1,322	389	10.809	18.932	0.376
Temporal holdout	Ridge	1,322	389	14.214	19.868	0.312
Temporal holdout	Mean benchmark	1,322	389	15.736	24.299	−0.029
Random observation split	Mean benchmark	1,368	343	14.939	21.859	−0.001
Random observation split	Ridge	1,368	343	10.385	16.635	0.420
Random observation split	Random Forest	1,368	343	3.874	5.701	0.932
Random observation split	Extra Trees	1,368	343	3.197	4.938	0.949
Random observation split	Gradient Boosting	1,368	343	8.238	15.569	0.492

Source(s): Computations from the study dataset (2026)

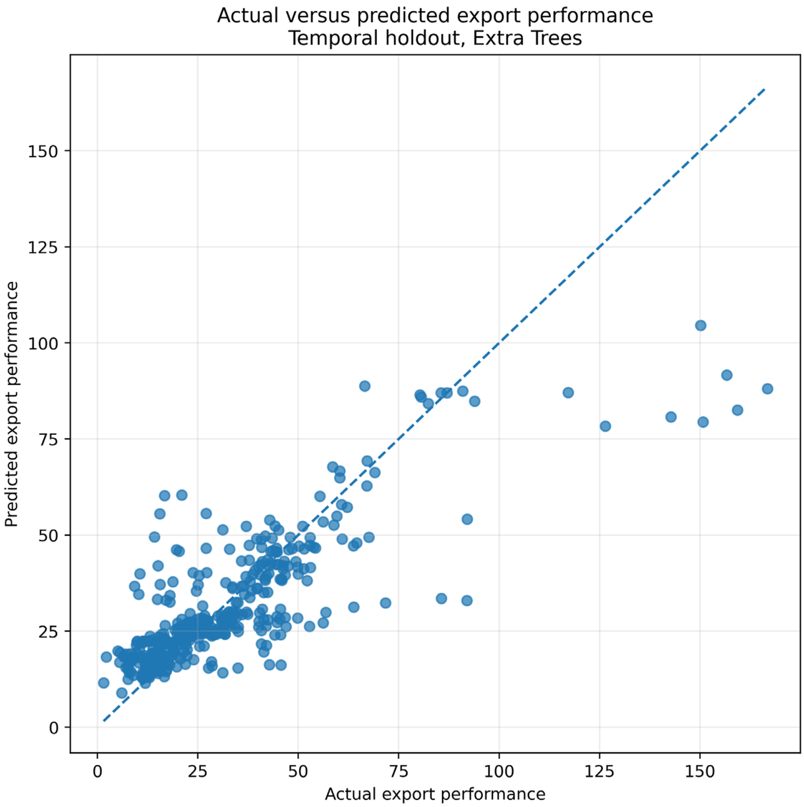

Figure 3. Actual versus predicted export performance under temporal validation. Source: Computations from the study dataset (2026)

4.3 Expanded and direct-logistics robustness results

Adding production-cost, trade-facilitation, transport and export-capacity indicators raises temporal *R*-squared from 0.651 to 0.667 and reduces RMSE from 14.149 to 13.845. The direct-logistics specification records R-squared of 0.809 and RMSE of 10.738, but it is based on 467 rows from intermittent measurement years. Its higher accuracy is therefore interpreted as evidence that direct logistics information is valuable, not as proof that the sparse specification is universally superior. (See Table 5).

4.4 Subregional predictive heterogeneity

Temporal errors are lowest in Southern Africa and West Africa, while East Africa records the highest RMSE. Bias also changes sign across subregions. These results show that pooled accuracy does not imply uniform performance and that regional structure remains important after conditioning on observed features. (See Table 6).

4.5 Permutation importance and SHAP patterns

The overall permutation ranking is dominated by controls: log GDP per capita, log population, subregion and services value added. Among direct readiness indicators, industry employment ranks highest, followed by electricity access and private-sector credit. This separation matters because a variable can be highly predictive without representing a direct or feasible policy lever. (See Table 7).

The SHAP ranking similarly places log GDP per capita first, followed by log population, natural-resource rents, Southern Africa, services value added and electricity access. The dependence plots reveal nonlinear and interacting patterns. Higher income contributes increasingly positive predictions at the upper end of the distribution; larger population tends to contribute negatively after other features are considered; and resource rents are flat or negative through much of the range but become strongly positive among high-rent observations. The interaction colouring indicates that these patterns vary with income and population rather than operating independently. (See Figures 4–6). (See Supplementary Figures S9, S10a, S10b, S10c and S10d).

Table 5. Temporal performance across core, extended and direct-logistics specifications

Specification	Rows	Countries	First year	Last year	Cutoff	Best model	R-squared	RMSE
Core annual readiness	1,711	51	1985	2024	2017	Extra Trees	0.651	14.149
Extended readiness	1,711	51	1985	2024	2017	Extra Trees	0.667	13.845
Direct logistics readiness	467	51	2007	2022	2018	Extra Trees	0.809	10.738

Source(s): Computations from the study dataset (2026)

Table 6. Temporal prediction errors by African subregion

Subregion	N	MAE	Bias	RMSE
Central Africa	72	10.154	−0.785	14.972
East Africa	120	10.630	2.468	18.446
North Africa	46	10.167	3.480	16.407
Southern Africa	40	4.906	−1.641	6.953
West Africa	111	5.713	0.173	7.703

Source(s): Computations from the study dataset (2026)

Table 7. Top permutation contributions in the core temporal model

Feature	Importance	SD
GDP per capita, log	0.3666	0.0395
Population, log	0.1994	0.0335
African subregion	0.1313	0.0136
Services value added	0.1177	0.0121
Industry employment	0.0899	0.0047
Natural-resource rents	0.0391	0.0063
Island status	0.0235	0.0076
Electricity access	0.0218	0.0038
Private-sector credit	0.0199	0.0035
Population density	0.0096	0.0009

Source(s): Computations from the study dataset (2026)

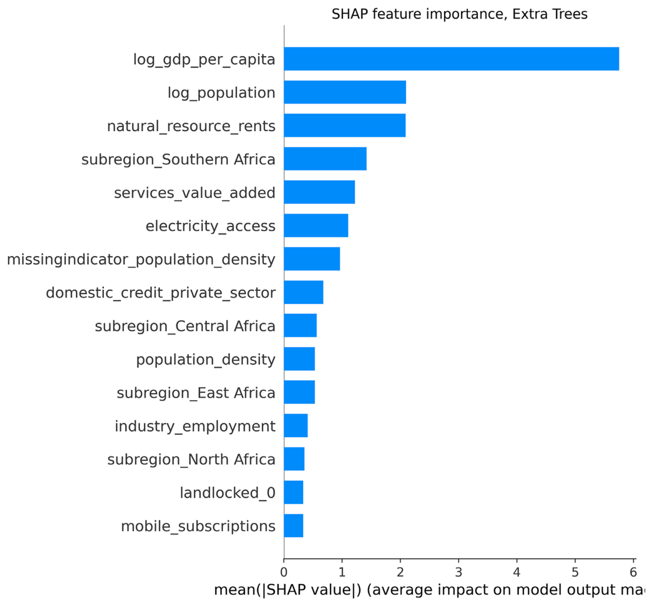

Figure 4. SHAP feature importance for the preferred temporal model. Source: Computations from the study dataset (2026)

4.6 Fixed-effects benchmark

The country-and-year fixed-effects benchmark uses 798 complete observations from 46 economies. Lagged inflation and services value added are negatively associated with export intensity, while natural-resource rents are positively associated. Most direct readiness variables are statistically imprecise in this smaller complete-case sample. The difference from the machine-learning ranking illustrates that out-of-sample predictive contribution and within-country conditional association answer different questions. (See Table 8).

4.7 Readiness clusters

A three-cluster solution has the highest silhouette score (0.421). The first three principal components explain 81.89% of the variance in the readiness indicators. Cluster 0 contains 15

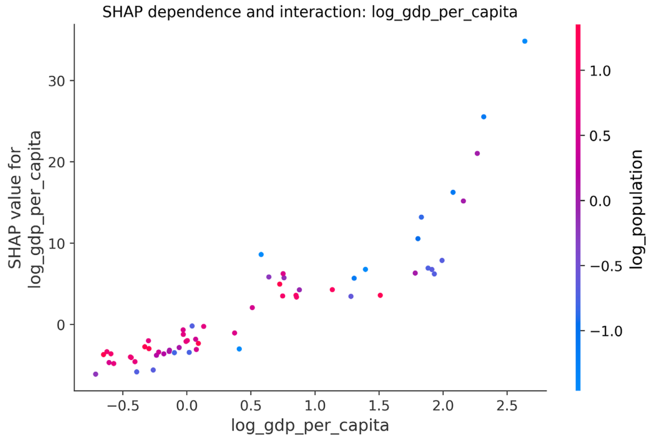

Figure 5. SHAP dependence and interaction pattern for GDP per capita. Source: Computations from the study dataset (2026)

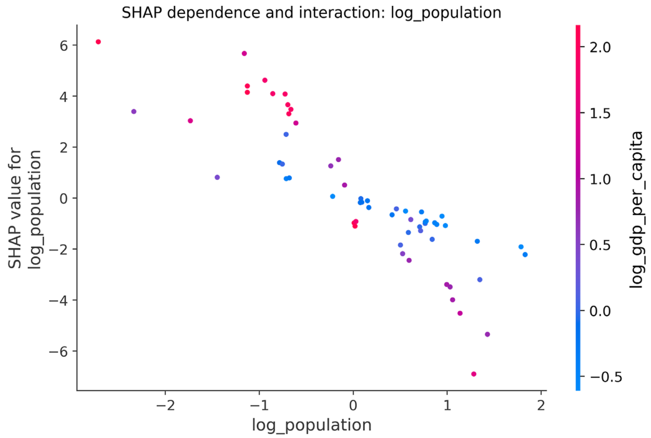

Figure 6. SHAP dependence and interaction pattern for population. Source: Computations from the study dataset (2026)

higher-readiness economies; Cluster 1 contains 38 lower-readiness economies; and Cluster 2 contains one extreme case, the Democratic Republic of the Congo, whose profile is dominated by very high average inflation. The third cluster is therefore treated as an outlier profile rather than a general readiness regime. (See Table 9 and Figure 7). (See Supplementary Tables S6a, S6b and S7; Supplementary Figure S7).

4.8 Alternative export-performance margins, missing-data sensitivity and within-country structure

The alternative outcomes show that the predictive pattern is not confined to exports as a share of GDP. Extra Trees records *R*-squared of 0.926 for log merchandise export value, 0.891 for the number of exported HS-6 products and 0.824 for log export value per HS-6 product. These results cover aggregate export scale, product breadth and product depth, respectively. The destination-partner measures are not estimated because the retrieved partner series did not

Table 8. Country and year fixed-effects benchmark with lagged core predictors

Variable	Coefficient	Standard error	*p*-value
Internet use, lagged	−0.095	0.080	0.234
Mobile subscriptions, lagged	0.002	0.031	0.937
Electricity access, lagged	−0.013	0.081	0.876
Manufacturing value added, lagged	−0.110	0.159	0.490
Industry employment, lagged	0.357	0.218	0.101
Private-sector credit, lagged	0.046	0.077	0.549
Inflation, lagged	−0.036	0.007	<0.001
Log GDP per capita	−0.196	2.713	0.942
Log population	−18.695	10.210	0.067
Population density	0.030	0.047	0.525
Services value added	−0.402	0.134	0.003
FDI inflows, lagged	0.019	0.054	0.727
Natural-resource rents	0.560	0.165	<0.001

Note(s): Country and year effects are included; standard errors are clustered by country. The estimates are associational

provide usable country-year coverage and were not reconstructed through imputation (See Table 10 and Figure 8). (See Supplementary Tables S8 and S9; Supplementary Figures S11, S12 and S13).

The missing-data sensitivity test also changes the interpretation of the benchmark. The complete-case Extra Trees model, estimated on 630 training observations and 202 later-period observations with no numerical imputation, records MAE = 6.869, RMSE = 11.677 and R-squared = 0.737. This is higher than the pooled benchmark R-squared of 0.651, indicating that the benchmark signal is not created by median imputation. The result does not make sparse variables harmless; rather, it supports the 50% eligibility rule used for the bridge analyses and the separation of sparse logistics indicators into dedicated period-specific tests. (See Supplementary Tables S10 and S11).

Country demeaning provides a direct test of whether pooled machine learning is mainly learning persistent country differences. R-squared falls from 0.651 to 0.242 for export intensity and from 0.926 to 0.283 for log merchandise export value. The decline confirms that a substantial share of pooled predictive accuracy is between-country structural information. Importantly, the within-country rankings are not empty. Industry employment is the largest readiness contribution for within-country export intensity (permutation importance = 0.270). For within-country log merchandise exports, manufacturing value added is the leading readiness contribution (0.104), followed by mobile subscriptions (0.028), industry employment (0.027), private-sector credit (0.017) and internet use (0.015). (See Table 11). (See Supplementary Tables S11, S12 and S13).

5. Discussion

The first finding is conceptual in the sense that export intensity can be predicted from a combination of readiness indicators and structural controls, but it should not be labelled export competitiveness. Renaming the outcome clarifies that the analysis concerns the share of domestic activity connected to exports rather than relative product advantage, sophistication or complexity.

The second finding concerns outcome and variable design. Removing imports, current account balance and the trade aggregate eliminates the principal source of accounting and trade-openness overlap, while the alternative outcomes show that the empirical story is not dependent on the exports-to-GDP ratio. Strong temporal performance for log merchandise

Table 9. Mean country profile by readiness cluster

Cluster	Countries	Internet	Electricity	Manufacturing VA	Industry employment	Private credit	Inflation	Export performance
0	15	26.56	77.25	12.87	22.12	39.91	6.46	38.00
1	38	8.67	31.04	9.51	11.06	12.62	22.88	27.97
2	1	4.73	14.46	12.44	8.39	3.55	1094.54	29.00

Source(s): Computations from the study dataset (2026)

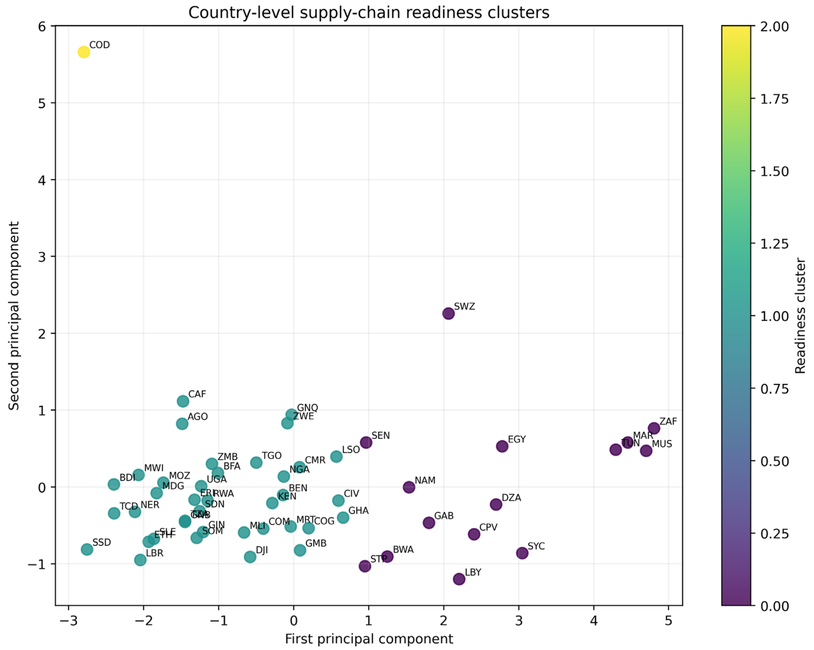

Figure 7. Country-level PCA map of supply-chain readiness clusters. Source: Computations from the study dataset (2026)

Table 10. Alternative export-performance outcomes under temporal validation

Outcome	Observed N	Countries	Period	Best model	*R*-squared	RMSE
Aggregate value — log merchandise exports	1,962	54	1988–2024	Extra Trees	0.926	0.507
Extensive margin — export partners	–	–	–	Not estimated	–	–
Extensive margin — exported HS6 products	1,185	49	1990–2023	Extra Trees	0.891	334.676
Intensive margin — log exports per partner	–	–	–	Not estimated	–	–
Intensive margin — log exports per HS6 product	1,185	49	1990–2023	Extra Trees	0.824	0.629

Note(s): Partner-based breadth and depth outcomes did not meet usable coverage and were not filled by imputation
Source(s): Computations from the study dataset (2026)

export value, exported HS-6 product breadth and export value per HS-6 product indicates that readiness and structural conditions contain information about export scale, breadth and depth. The inability to estimate the partner-based margins is treated as a data-coverage limitation rather than resolved through imputation. The broader outcome design is consistent with evidence that African export performance reflects structural, trade and policy conditions beyond a single openness ratio (Vogel, 2025).

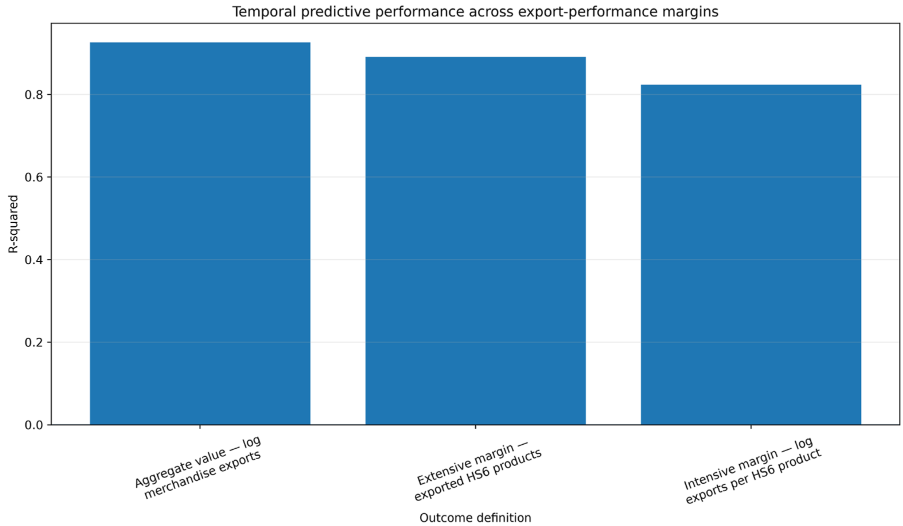

Figure 8. Temporal predictive performance across estimable export-performance margins. Source: Computations from the study dataset (2026)

Table 11. Pooled, complete-case and within-country predictive diagnostics

Outcome/diagnostic	Model scope	R-squared	RMSE
Export intensity benchmark	Pooled levels ML	0.651	14.149
Export intensity benchmark	Complete case; no numerical imputation	0.737	11.677
Export intensity benchmark	Within-country ML	0.242	10.510
Log merchandise export value	Pooled levels ML	0.926	0.507
Log merchandise export value	Within-country ML	0.283	0.627

Source(s): Computations from the study dataset (2026)

The third finding is that the largest predictive contributions come from controls. Income, population, subregion, services and resource dependence capture broad heterogeneity in productive structure and export composition. Their importance should not be translated directly into a policy ranking. Among direct readiness measures, industry employment, electricity access and private credit are more defensible intervention-related signals, although their permutation contributions are smaller.

The SHAP results add information beyond ranking. The income pattern is nonlinear, the population pattern is generally negative after other conditions are held constant, and high resource rents are associated with unusually positive export-intensity predictions. The resource-rent pattern is consistent with large commodity-export shares but does not imply diversified or sophisticated export structures. This distinction helps reconcile high export intensity with continuing concerns about concentration and structural transformation in Africa (Avenyo *et al.*, 2021; Vogel, 2025).

The fixed-effects and country-demeaned results provide a stronger caution than a simple distinction between prediction and inference. The pronounced fall in R-squared after country demeaning confirms that pooled machine learning learns substantial between-country structure. That structural component is useful for cross-country prediction but cannot be interpreted as evidence that changing a high-ranked level variable within a country will reproduce the pooled ranking. At the same time, industry employment remains the strongest readiness signal for within-country export intensity, while manufacturing value added leads the readiness variables for within-country merchandise export value. The two approaches are therefore complementary only when the between-country component is made explicit.

6. Policy implications

Policy interpretation should begin with mechanisms rather than the pooled feature ranking. Electricity access affects production continuity, cold-chain reliability and the ability to meet delivery schedules. Industrial employment and manufacturing value added proxy the depth of productive capabilities and supplier networks that allow more products to reach exportable scale. Private-sector credit supports working capital, certification, inventory and shipment finance, while digital connectivity reduces buyer-search, coordination, documentation and tracking costs. Border time, shipping connectivity and logistics competence operate through lead-time reliability and the amount of capital tied up while goods move across borders. These pathways link readiness to both export breadth and export depth.

The within-country diagnostics narrow the actionable interpretation. Industry employment is the strongest readiness signal for within-country movements in export intensity, and manufacturing value added is the strongest readiness signal for within-country changes in log merchandise exports. These results suggest that governments should first diagnose whether the binding constraint is productive capacity, finance, energy, digital coordination or border/logistics reliability, and then compare interventions within that constraint. A country with repeated power interruptions may obtain little from advanced tracking systems until production reliability improves; a country with adequate production but high border delays may obtain more from customs process reform and corridor coordination.

The machine-learning results do not determine budget allocations on their own. A practical prioritisation process should combine the within-country readiness signals with intervention cost, implementation time, corridor exposure, distributional effects and credible causal evidence from pilots or quasi-experimental evaluation. Structural controls such as GDP per capita, population, subregion and island status remain useful for identifying context, but they are not investment levers. This converts explainable machine learning from a causal ranking into a screening tool for selecting bottlenecks that warrant economic appraisal.

7. Conclusion

This study examines supply-chain readiness and export performance across African economies using an interpretable predictive framework. Export intensity is retained as a benchmark, while log merchandise export value, exported HS-6 product breadth and log export value per HS-6 product provide alternative measures of aggregate scale, extensive product breadth and intensive product depth. Trade, imports and current account balance remain excluded from the main specifications, and direct readiness measures are separated from structural controls.

Extra Trees provides the strongest benchmark temporal result, with R-squared of 0.651. The alternative outcome models record R-squared of 0.926 for log merchandise exports, 0.891 for exported HS-6 product breadth and 0.824 for log exports per HS-6 product. A complete-case benchmark without numerical imputation records R-squared of 0.737. Country demeaning lowers predictive performance to 0.242 for export intensity and 0.283 for log merchandise exports, demonstrating that pooled results contain substantial between-country structure. Within-country importance nevertheless identifies industry employment and manufacturing value added as the leading readiness signals for the two principal outcomes.

These limitations provide a clear direction for future research. The destination-partner breadth and per-partner depth measures did not provide a usable country-year series in the retrieved WITS indicators and should be reconstructed directly from bilateral Comtrade records in future work. Product-level measures such as revealed comparative advantage, EXPY, economic complexity, export diversification and constant-market-share performance can further distinguish export quality from scale. Shipment-level logistics measures, structural-break tests, alternative missing-data strategies, firm and corridor evidence, and credible causal designs are also required before estimating the return to specific customs, infrastructure, energy or digital interventions.

Data availability

The data and analytical code used in this study are available at the Mendeley Data repository (https://data.mendeley.com/preview/3gg5mxhxwp).

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Supplementary material

The supplementary material for this article can be found online.

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