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ARTIFICIAL INTELLIGENCE ADOPTION AND EXPORT QUALITY UPGRADING ACROSS MANUFACTURING FIRMS

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Abstract:

This study examines whether changes in manufacturing export technology intensity represent broadly distributed structural upgrading and how artificial intelligence adoption varies across industries, contributing to international debates on technological transformation. Using 165 annual observations from 15 economies covering 2010 to 2020 and United States manufacturing artificial intelligence estimates for 2016 to 2018, the study applies descriptive comparative analysis, percentage point decomposition, industry comparisons, and sensitivity analysis. The average high technology export share increased by 1.680 percentage points, although nine economies experienced declines. Excluding Viet Nam reversed the average change to negative 0.243 percentage points, demonstrating substantial concentration. Manufacturing production artificial intelligence adoption averaged 3.080 percent across 15 industries, while moderate or high adoption averaged only 1.507 percent. Electrical equipment recorded the highest adoption at 5.4 percent, revealing pronounced industrial heterogeneity. The findings refine technological upgrading frameworks by distinguishing export composition, adoption breadth, and deployment intensity. International industrial policies should therefore prioritize distribution sensitive performance indicators and differentiated technological deployment assessments over aggregate measures of manufacturing progress.

Key Words: Artificial Intelligence Adoption; Manufacturing Transformation; Export Technology Intensity; Industrial Heterogeneity; Technological Upgrading.

1. Introduction:

Manufacturing transformation is difficult to assess when technological adoption, export composition, and product quality are treated as equivalent outcomes. A larger share of technology intensive exports may reflect changes in the products traded without establishing improvements in quality within those products. Likewise, reported artificial intelligence adoption identifies technological use without demonstrating its contribution to export performance. These distinctions matter for manufacturers allocating investment and for governments assessing whether industrial development reflects broader productive capabilities or concentrated changes in export structure.

Research on international trade establishes that quality differentiation shapes manufacturing competitiveness, but its measurement requires more than a technological classification of exports. Khandelwal (2010) estimates quality through demand information that distinguishes product appeal from price, while Hallak and Schott (2011) separate quality differences from other determinants of trade outcomes. Kugler and Verhoogen (2012) connect input quality, output quality, and plant size, demonstrating that manufacturing differentiation involves complementary production choices. Hallak and Sivadasan (2013) further distinguish product productivity from process productivity. Together, these contributions show why improvements in production efficiency, export technology intensity, and product quality require separate empirical interpretation.

Digital transformation research provides a complementary explanation of how technological resources may contribute to manufacturing performance. Bharadwaj et al. (2013) emphasize the integration of digital technologies with business strategy, while Nambisan et al. (2017) examine how digitalization changes innovation processes and organizational arrangements. Tambe et al. (2012) show that information technology returns depend on complementary information practices and decision structures. This reasoning distinguishes technological infrastructure, organizational capabilities, and operational applications. Infrastructure provides technical capacity, capabilities support its effective use, and operational applications embed technology within production activities. These mechanisms motivate expectations about manufacturing upgrading, but evidence concerning digital technologies generally does not establish an AI specific relationship with export quality.

The distinction between adoption and deployment also matters within manufacturing. A company reporting limited production use occupies a different technological position from one reporting moderate or high use. Combining these categories can obscure the intensity of technological application. Acemoglu and Restrepo (2019) explain technological change through the allocation of production tasks, directing attention toward what technologies perform rather than their acquisition alone. Cirera and Maloney (2017) similarly emphasize the capabilities required to translate technological opportunities into productive applications. These perspectives support examining adoption breadth and intensity separately, while keeping proposed capability mechanisms distinct from directly observed adoption categories.

The closest empirical literature also demonstrates the importance of matching claims to observation units. Manova and Zhang (2012) document variation in export prices across firms and destinations, illustrating the information lost when national aggregates substitute for exporter records. Graetz and Michaels (2018) estimate productivity effects from industrial robot use through a design that links technological exposure to economic outcomes. Their findings concern a specific technology and outcome and cannot establish effects of AI on export quality. The reviewed evidence therefore provides explanations for technological complementarity and quality differentiation, while leaving a separate descriptive question: how concentrated are changes in export technology intensity, and how does reported AI deployment vary across manufacturing industries?

This study aims to characterize the concentration of manufacturing export restructuring and distinguish the breadth of production AI adoption from its reported intensity. The analysis asks whether increasing average export technology intensity represents broadly shared change across the selected economies and how manufacturing industries differ in production AI use. Its objectives are to measure national export share changes, assess the influence of individual country trajectories on the international average, and compare overall production use with moderate or high use across industries. These objectives align the empirical contribution with the available observations.

The empirical design combines two separate evidence blocks. The first contains 165 annual observations for 15 economies covering 2010 to 2020. It uses World Development Indicators to describe export composition and its economic context. The second contains published United States manufacturing AI estimates covering 2016 to 2018, comprising 18 industry groups and one sector aggregate. Fifteen industry groups disclose all components required for the adoption calculations. The analysis applies descriptive statistics, annual and endpoint share differences, adoption category sums, and an exploratory sensitivity calculation. National export indicators and industry adoption estimates retain their distinct units and reference periods.

The findings contribute by showing why international averages and aggregate adoption rates require distributional interpretation. The average high technology export share increases across the selected economies, although nine of the 15 record endpoint declines. Excluding Viet Nam reverses the direction of the average change. Manufacturing AI estimates independently reveal differences between adoption breadth and deployment intensity. The contribution is therefore a documented distinction among concentrated export restructuring, production adoption, and intensive use. For international audiences, this distinction supports more precise comparisons across economies and industries. For decision makers, it supports reporting the distribution of export trajectories and the intensity of technological deployment before attributing manufacturing progress to AI.

2. Theoretical and Conceptual Framework and Hypotheses Development:

2.1. Theoretical Foundation of Artificial Intelligence Adoption and Export Quality Upgrading:

Artificial intelligence adoption can strengthen manufacturing competitiveness by improving information processing, production coordination, and operational decision making. The resource-based perspective explains why firms with different technological resources and organizational capabilities achieve different performance outcomes. Dynamic capabilities theory extends this argument by emphasizing the capacity to integrate technological resources, adapt production processes, and respond to changing market requirements. Bharadwaj et al. 2013 established the strategic importance of digital technologies in transforming business activities, while Nambisan et al. 2017 explained how digital technologies reshape innovation processes and organizational boundaries.

Export quality upgrading refers to improvements in the characteristics, sophistication, and market valuation of products supplied to international markets. International competition creates incentives for manufacturers to improve product quality, satisfy buyer requirements, and differentiate their products. Kugler and Verhoogen 2012 demonstrated the relationship between firm size, input quality, and output quality in manufacturing, while Hallak and Sivadasan 2013 showed how product quality influences exporting behavior. These findings establish the economic relevance of quality differentiation but do not demonstrate that artificial intelligence adoption independently produces export quality improvements.

This analysis distinguishes three dimensions of artificial intelligence adoption: technological infrastructure, organizational capabilities, and operational applications. Technological infrastructure concerns the availability and integration of AI systems. Organizational capabilities capture the human and managerial resources required to deploy those systems. Operational applications concern the use of AI within production, quality control, and supply chain activities. These dimensions represent complementary mechanisms rather than interchangeable measures of technological adoption.

The proposed relationships are theoretical expectations. Their empirical interpretation depends on whether comparable firm level observations are available for the relevant constructs. Associations cannot establish causality without an identification strategy that addresses selection, confounding, and reverse causality.

2.2. AI Technological Infrastructure and Export Quality Upgrading:

AI technological infrastructure refers to the integration of intelligent software, automated systems, and analytical technologies into manufacturing activities. Such infrastructure can improve the availability,

processing, and application of production information. Bharadwaj et al. 2013 explain how digital technologies reshape business processes and organizational capabilities, while Nambisan et al. 2017 identify digital technologies as important mechanisms for transforming innovation processes. Technological infrastructure therefore provides a potential foundation for improving manufacturing quality rather than a sufficient condition for achieving superior export performance.

Manufacturing exporters face quality requirements concerning product consistency, technical specifications, and reliability. AI infrastructure may help firms identify production deviations, analyze quality information, and coordinate corrective decisions. These capabilities can reduce information constraints associated with product upgrading. However, investments in technological infrastructure may generate limited quality improvements when implementation is incomplete or existing production processes cannot use the resulting information. Hallak and Sivadasan 2013 distinguish process productivity from product productivity, demonstrating why improvements in production efficiency do not necessarily imply equivalent improvements in product quality.

The expected relationship follows the complementarity between technological resources and productive capabilities. Tambe et al. 2012 find that information technology contributes to organizational performance through complementary information practices and decision structures. Kugler and Verhoogen 2012 establish the importance of input and output quality choices in manufacturing, while Hallak and Sivadasan 2013 demonstrate the relevance of quality differentiation for exporting firms. Together, these findings support a positive theoretical association between technological infrastructure and export quality upgrading, although they do not directly establish an AI specific effect.

H1: Higher AI technological infrastructure is positively associated with export quality upgrading among manufacturing exporters.

2.3. AI Organizational Capabilities and Export Quality Upgrading:

AI organizational capabilities represent the workforce competencies, investment resources, and managerial arrangements through which firms implement intelligent technologies. Unlike technological infrastructure, which concerns the availability of technological systems, organizational capabilities determine whether firms can translate technological resources into productive decisions. The digital business strategy perspective emphasizes the integration of technological and organizational activities, while research on digital innovation highlights changes in coordination and innovation management associated with digitalization. These arguments suggest that technological investment alone cannot explain differences in export quality upgrading.

Organizational capabilities may influence export quality through employee competence, resource allocation, and management commitment to quality improvement. Skilled personnel can interpret technological outputs and translate analytical information into production decisions. Management support can align technological applications with product specifications and export market requirements. Nevertheless, organizational investments may impose adjustment costs and compete with other productive expenditures. Consequently, their contribution to export quality depends on whether firms develop complementary processes that convert technological knowledge into improvements in exported products.

Tambe et al. 2012 provide empirical evidence that organizational practices and information technology investments are complementary in explaining innovation and productivity. Bharadwaj et al. 2013 further establish the strategic importance of integrating digital resources with business processes. Nambisan et al. 2017 explain how digitalization changes the organization of innovation, while Kugler and Verhoogen 2012 and Hallak and Sivadasan 2013 demonstrate the importance of firm capabilities and quality choices in manufacturing and international trade. This evidence supports the expectation that stronger AI organizational capabilities are associated with improved export quality, subject to effective technological implementation.

H2: Higher AI organizational capabilities are positively associated with export quality upgrading among manufacturing exporters.

2.4. AI Operational Applications and Export Quality Upgrading:

AI operational applications refer to the use of intelligent technologies in quality control, production optimization, and supply chain management. This dimension concerns the practical deployment of technological resources within manufacturing operations. Whereas technological infrastructure establishes technical capacity and organizational capabilities facilitate implementation, operational applications connect intelligent technologies directly to production activities. Digital innovation theory suggests that technological value emerges through changes in processes and organizational practices rather than technology acquisition alone.

AI based quality control may improve defect detection and consistency in manufacturing outputs. Production optimization may strengthen process stability, while intelligent supply chain management may improve coordination of material requirements and production schedules. These mechanisms can support export quality upgrading by improving firms' capacity to meet product specifications. However, operational efficiency and export quality remain distinct outcomes. Faster production, lower costs, or improved logistics do not necessarily establish improvements in product sophistication, compliance, or quality valuation.

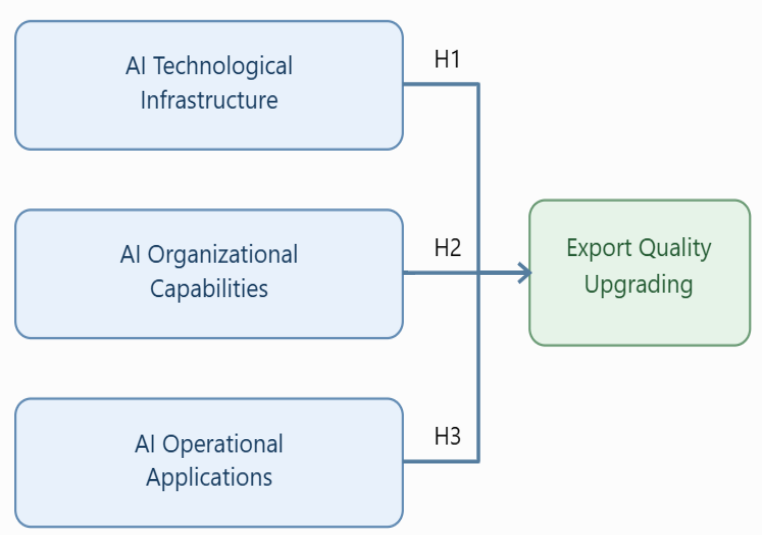
Hallak and Sivadasan 2013 demonstrate that product quality and process productivity represent distinct dimensions of manufacturing competitiveness. Kugler and Verhoogen 2012 show that manufacturing quality choices involve relationships between production inputs and output characteristics. Tambe et al. 2012 establish the relevance of information practices to innovation and productivity, while Bharadwaj et al. 2013 and Nambisan et al. 2017 provide theoretical foundations for understanding technology enabled operational transformation. These contributions support a positive expected relationship between AI operational applications and export quality upgrading, without establishing that all operational improvements translate into higher export quality.

H3: Greater AI operational application is positively associated with export quality upgrading among manufacturing exporters.

2.5. Conceptual Framework:

The conceptual framework specifies three theoretically distinct dimensions of artificial intelligence adoption as predictors of export quality upgrading. The proposed relationships reflect positive associations rather than established causal effects. Each hypothesis requires comparable measurements from the same manufacturing firms and observation periods. The framework does not assume that technological infrastructure, organizational capabilities, or operational applications can be represented by a validated composite index without additional measurement evidence.

Figure 1: Theoretical associations between AI adoption dimensions and export quality upgrading. H1, H2, and H3 represent proposed positive relationships, not empirically confirmed effects.



3. Data:

This analysis documents data provenance, sample construction, variable measurement, and the calculations used to describe manufacturing exports and artificial intelligence adoption. It retains the distinction between annual national indicators and manufacturing industry adoption estimates.

3.1 Data Sources, Population, and Sample Construction:

The country panel contains seven World Development Indicators series for 15 economies over 2010 to 2020. High technology exports as a percentage of manufactured exports measure technology intensity in export composition, while manufactured exports as a percentage of merchandise exports describe manufacturing concentration. Manufacturing value added as a percentage of GDP provides sectoral context (World Bank, n.d.-e, n.d.-f, n.d.-g). The selected economies are Brazil, Canada, China, France, Germany, India, Italy, Japan, Mexico, the Republic of Korea, Rwanda, South Africa, the United Kingdom, the United States, and Viet Nam. Selection provides illustrative manufacturing and geographical coverage rather than a probability sample. The accessible frame contains 165 country year observations across 11 annual periods.

Artificial intelligence adoption comes from Table 84 of the Annual Business Survey, survey cycle 2019 and data year 2018. The National Center for Science and Engineering Statistics and the United States Census Bureau provide the underlying statistics. The reference period covers 2016 to 2018. The extracted manufacturing block contains 18 mutually exclusive industry groups and one sector aggregate. The aggregate represents an estimated 217,565 companies rather than the number of survey respondents (National Center for Science and Engineering Statistics, n.d.). National indicators were extracted through the World Bank Indicators API, while AI percentages were extracted from the official statistical table. The accompanying workbook retains exact query URLs, source update metadata, extraction documentation, and response hashes. World Bank data are distributed under Creative Commons Attribution 4.0, subject to additional provider attribution requirements (World Bank, n.d.-b).

Table 1: Sample construction and coverage

Stage	Units	Observations	Implemented Rule
Selected country frame	15 economies	165 country year records	Annual observations from 2010 to 2020
Consolidated source extraction	15 economies	1,155 indicator records	Seven series for each country year
Retained country panel	15 economies	165 country year records	Preserve all selected country years
Complete indicator coverage	15 economies	150 country year records	All seven indicators observed
Annual export share changes	15 economies	150 changes	Current and preceding annual shares available
Extracted manufacturing AI block	18 industries and one aggregate	19 period records	One observation per unit covering 2016 to 2018
Industry comparison frame	18 industries	18 period records	Keep the overlapping aggregate separate
Calculable industry production AI use	15 industries	15 period records	All required adoption components disclosed

The country frame is balanced in identifiers and annual coverage, although research expenditure has incomplete measurement coverage. The AI dataset is a cross section covering a multiyear reference period. Its observations are not replicated across individual years.

3.2 Data Integration, Cleaning, and Quality Assurance:

The national series were aligned using ISO3 country identifiers and calendar year. Each country year contains seven source indicator records. Verification identified no duplicate country, year, and indicator combinations. Consolidated values matched their corresponding source cells. Extraction used the country, indicator, and date query structure documented by the World Bank (n.d.-a).

Original units were preserved. Fixed broadband remains subscriptions per 100 people, and GDP per capita remains in constant 2015 United States dollars (World Bank, n.d.-c, n.d.-d). Research expenditure and trade remain percentages of GDP (World Bank, n.d.-h, n.d.-i). No additional currency conversion, inflation adjustment, or frequency conversion was applied.

Six national indicators contain 165 observed values each. Research expenditure contains 150 observed values and 15 source gaps. Rwanda accounts for nine gaps in 2010 to 2015, 2017, 2018, and 2020. Viet Nam accounts for six gaps in 2010, 2012, 2014, 2016, 2018, and 2020. All country year rows were retained, with source gaps left blank.

The AI block contains five suppressed component percentages across beverage and tobacco products, textile products, paper, and petroleum products. These values remain blank with their disclosure flags. Nineteen component estimates retain the source flag identifying relative standard errors above 50 percent. Derived adoption shares remain blank whenever a required component is suppressed.

Checks confirmed that export shares, manufacturing shares, and observed research expenditure percentages lie between zero and 100. Broadband, income, and trade values are nonnegative. Trade openness was not capped at 100 because exports plus imports can exceed GDP. The 15 fully disclosed AI category distributions sum to 100 at the published precision. Observed values were retained without interpolation, trimming, winsorization, or replacement of missing values by zero.

3.3 Variable Measurement, Construction, and Validation:

The analysis measures export composition and production AI use at their observed aggregation levels. Export category shares are distinguished from product quality because quality estimation requires additional information on prices, quantities, demand, or product characteristics (Hallak & Schott, 2011; Khandelwal, 2010). Input quality and plant characteristics also affect observed product differentiation (Kugler & Verhoogen, 2012). Process productivity remains conceptually distinct from product quality, while export prices vary across firms and destinations (Hallak & Sivadasan, 2013; Manova & Zhang, 2012).

Table 2: Variable dictionary

Variable or indicator	Analytical role	Definition and construction	Source and identifier	Unit and frequency	Transformation and direction	Missing value rule	Coverage and limitation
High technology export share	Export composition measure	High technology exports divided by manufactured exports, multiplied by 100	World Bank, TX.VAL.TECH.MF.ZS	Percent, annual	Source level retained; higher values indicate greater technology intensity	Preserve source blanks	165 values; measures export composition
Manufactured export share	Export structure indicator	Manufactured exports divided by merchandise exports, multiplied by 100	World Bank, TX.VAL.MANF.ZS.UN	Percent, annual	Higher values indicate greater manufacturing concentration	Preserve source blanks	165 values
Manufacturing value added	Sectoral context	Manufacturing value added divided by GDP, multiplied by 100	World Bank, NV.IND.MANF.ZS	Percent, annual	Higher values indicate greater manufacturing intensity	Preserve source blanks	165 values
Fixed	Digital	Fixed broadband	World Bank,	Subscriptions	Higher values	Preserve	165 values;

Variable or indicator	Analytical role	Definition and construction	Source and identifier	Unit and frequency	Transformation and direction	Missing value rule	Coverage and limitation
broadband	infrastructure context	subscriptions per 100 people	IT.NET.BBND.P2	per 100 people, annual	indicate greater subscription penetration	source blanks	national measure
Research expenditure	Innovation context	Research expenditure divided by GDP, multiplied by 100	World Bank, GB.XPD.RSDV.GD.ZS	Percent, annual	Higher values indicate greater research intensity	Retain source blanks	150 values
GDP per capita	Income context	GDP per person in constant 2015 United States dollars	World Bank, NY.GDP.PCAP.KD	Constant dollars, annual	Higher values indicate greater real income	Preserve source blanks	165 values
Trade openness	International integration context	Exports plus imports divided by GDP, multiplied by 100	World Bank, NE.TRD.GNFS.ZS	Percent, annual	Higher values indicate greater trade relative to GDP	Preserve source blanks	165 values; may exceed 100
Annual export share change	Export composition change	Current high technology share less the preceding annual share within the same economy	Calculated from TX.VAL.TECH.MF.ZS	Percentage points, annual	Positive values indicate an increasing share	Require consecutive observations	150 changes
Production AI use	Operational adoption measure	Sum of low, moderate, and high production use percentages	Annual Business Survey, Table 84	Percent of companies, 2016 to 2018	Higher values indicate broader reported production use	Require all three components	15 industries plus the sector aggregate
Moderate or high AI use	Adoption intensity measure	Sum of moderate and high production use percentages	Annual Business Survey, Table 84	Percent of companies, 2016 to 2018	Higher values indicate greater reported use intensity	Require both components	15 industries plus the sector aggregate

AI measures add mutually exclusive response categories without normalization or additional weighting. Tested but unused technology and unknown responses remain outside production use. Annual export changes are percentage point differences rather than percentage growth rates.

Table 3: Presents unweighted descriptive statistics across available country year observations. Standard deviations use the sample definition

Indicator	Valid observations	Mean	Standard Deviation	Median	Minimum	Maximum
High technology export share	165	18.715	9.157	17.824	2.587	41.740
Manufactured export share	165	66.652	22.918	74.542	6.196	94.300
Manufacturing value added	165	15.878	6.502	14.132	6.782	31.562
Fixed broadband	165	22.423	14.893	27.465	0.025	46.471
Research expenditure	150	1.877	1.079	1.764	0.150	4.521
GDP per capita	165	23,869.904	18,497.414	29,470.673	579.419	61,047.965
Trade openness	165	59.310	28.569	56.588	22.772	164.704
Annual export share change	150	0.168	2.224	0.046	−10.870	8.348

Across the 15 industries with disclosed components, production AI use averages 3.080 percent, with a standard deviation of 1.370, a median of 3.100, and a range from 1.400 to 5.400. Moderate or high use averages 1.507 percent, with a standard deviation of 0.805, a median of 1.500, and a range from 0.400 to 3.100. These industry statistics exclude the overlapping manufacturing aggregate and apply equal industry weights.

3.4 Analytical Framework, Identification, and Reproducibility:

The implemented framework is descriptive. It examines national export composition over time and reported AI adoption across manufacturing industries. Calculations comprise source consolidation, annual share differences, adoption category sums, coverage counts, and descriptive statistics. This scope preserves the distinction between description, prediction, and causal explanation (Shmueli, 2010).

The country panel and industry cross section remain separate because their observation units and reference periods differ. Their comparison provides contextual evidence rather than an estimated effect of AI adoption on export quality. This interpretation follows the distinction between observed patterns and effects identified through a research design (Angrist & Pischke, 2010; Athey & Imbens, 2017).

The reproducibility record preserves source values, series identifiers, exact API requests, source update metadata, response hashes, disclosure flags, variable definitions, and editable construction formulas. Raw observations remain separate from calculated measures, allowing reported transformations to be traced to their inputs. This structure supports computational transparency and verification (Christensen & Miguel, 2018; Peng, 2011). Definitions, denominators, and timing remain consistent within each evidence block.

4. Methods:

4.1 Research Design and Analytical Scope:

This analysis uses a descriptive comparative design to examine the concentration of changes in manufacturing export composition and variation in production AI adoption. The national component draws on variation across 15 economies and annual observations from 2010 to 2020. The industry component compares published United States manufacturing adoption estimates covering 2016 to 2018. These components remain separate because they represent different observation units and reference periods.

The analytical targets are the distribution of national export share changes, the sensitivity of their average to an influential country trajectory, and differences between overall production AI use and moderate or high use. This design distinguishes description from causal explanation, consistent with Shmueli (2010). Its contribution rests on transparent comparisons at the observed aggregation levels rather than an estimate of the effect of AI on export quality.

4.2 Measurement and Calculation Procedures:

The sample construction table and variable dictionary define the observation frame, source measures, units, and coverage rules. National calculations retain the original percentage scales. Annual changes compare consecutive observations within the same economy, as specified in Equation 1.

$$\Delta H_{ct} = H_{ct} - H_{c,t-1}$$

Here, H_{ct} denotes the high technology export share for economy c in year t, and ΔH_{ct} denotes its annual change in percentage points. The calculation produces 150 changes because the initial observation for each economy has no preceding observation within the study period. Endpoint comparisons measure cumulative changes between the first and last observation years. Equation 2 defines the unweighted mean endpoint change.

$$D_c = H_{c,2020} - H_{c,2010}, \qquad \overline{D} = \frac{1}{C}\sum_{c=1}^{C} D_c$$

Here, D_c denotes the endpoint change for economy c, $\overline{D}$ denotes the mean change, and C denotes the number of included economies. The main comparison assigns equal weight to each of the 15 economies. Consequently, the mean describes the selected economies rather than the share of global manufacturing exports. Industry adoption measures add mutually exclusive response categories. Equation 3 distinguishes overall production use from moderate or high use.

$$A_s = L_s + M_s + U_s, \qquad I_s = M_s + U_s$$

Here, A_s denotes overall production AI use in industry s, I_s denotes moderate or high use, and L_s, M_s, and U_s denote the published percentages reporting low, moderate, and high use, respectively. Each measure is calculated only when every required component is disclosed. Tested but unused technology and unknown responses remain outside production use. These calculations preserve the distinction between export composition and product quality. A technological category share describes the products exported without identifying quality differences within those products. This interpretation follows the measurement distinctions developed by Hallak and Schott (2011) and Khandelwal (2010).

4.3 Sample Alignment, Processing, and Descriptive Analysis:

National observations were organized by ISO3 country identifier and calendar year. Seven indicator records were aligned with each country year, producing 165 consolidated observations. Original source values were preserved, while derived measures were stored separately. The first annual difference was left blank for each economy, and endpoint comparisons required observations for both endpoint years. Descriptive statistics use the available observations for each indicator. Means, medians, minima, maxima, and sample standard deviations summarize location and dispersion. Six indicators contain 165 observations each, while research expenditure contains 150. Missing values remain blank and do not trigger removal of otherwise observed country year records. Each reported summary therefore uses its own valid observation count.

Industry comparisons exclude the manufacturing aggregate because it overlaps the constituent industry groups. Both derived adoption measures are available for 15 of the 18 extracted groups. Industry summaries assign equal weight to these disclosed groups and retain the published sector aggregate as a separate estimate. Company population estimates are not treated as respondent counts or used to reconstruct survey weights. Workbook formulas implement the annual differences and adoption sums. Python calculations produce the descriptive summaries, endpoint comparisons, and sensitivity calculation. Calculations use unrounded source values; rounding is applied only when presenting results. Observed extremes remain in the main analysis without trimming, winsorization, or interpolation.

4.4 Verification, Sensitivity, and Reproducibility:

Verification assessed identifier uniqueness, alignment across indicators, agreement between source and consolidated values, permissible measurement ranges, and the arithmetic consistency of derived measures. Country, year, and indicator combinations were checked for duplicates. Percentage bounds were checked for export composition, manufacturing intensity, and research expenditure. Trade openness was assessed separately because exports plus imports can exceed GDP.

AI verification preserved disclosure suppression and uncertainty flags. Suppressed components remain blank, while disclosed estimates with relative standard errors above 50 percent retain their source flags. Category totals were checked only where all response percentages were available. These procedures assess transcription and arithmetic consistency without treating published estimates as error free. An exploratory sensitivity calculation evaluates whether the mean endpoint change depends on Viet Nam's comparatively large increase. Equation 2 is recalculated for the remaining 14 economies, with the measurement definition and endpoint years unchanged. Viet Nam remains in the main sample. The comparison isolates sensitivity to sample composition and does not constitute an alternative causal specification.

Interpretation focuses on direction, magnitude, dispersion, and sensitivity. Sample standard deviations describe observed variation rather than uncertainty around population effects. The comparisons therefore support descriptive conclusions within the selected observations, consistent with the distinction between empirical patterns and identification through research design emphasized by Angrist and Pischke (2010). The research workbook retains original values, series identifiers, exact API queries, source update metadata, response hashes, disclosure flags, measurement rules, and editable construction formulas. These records allow the calculations to be traced to their inputs. This approach supports the computational transparency discussed by Peng (2011) and Christensen and Miguel (2018).

5. Findings:

This analysis examines changes in manufacturing export composition across 15 economies and variation in production AI use across United States manufacturing industries. The findings establish the direction, magnitude, and concentration of the observed patterns. National export shares and industry adoption estimates retain their separate units of analysis. The export dataset contains 165 annual observations covering 2010 to 2020. High technology export shares measure the composition of manufactured exports rather than quality differences within individual products. This distinction matters because product quality estimation requires information beyond the technological classification of traded goods, including demand, prices, or product characteristics (Hallak & Schott, 2011; Khandelwal, 2010).

Across all country year observations, the high technology export share averages 18.715 percent, with a standard deviation of 9.157 and a median of 17.824. Its range, from 2.587 to 41.740 percent, indicates substantial differences in export composition. The unweighted country mean increases from 17.667 percent in 2010 to 19.348 percent in 2020, a gain of 1.680 percentage points. However, only six economies record an increase between the two endpoints, while nine record a decline. The positive aggregate change therefore reflects concentrated gains rather than a common shift across the selected economies.

Table 1: Changes in high technology exports as a percentage of manufactured exports

Economy	2010 Share, Percent	2020 Share, Percent	Change, Percentage Points
Brazil	12.590	11.350	−1.240
Canada	15.501	16.759	1.258
China	32.150	31.277	−0.874
Germany	16.890	15.503	−1.386
France	26.323	22.540	−3.783
United Kingdom	23.304	23.007	−0.296
India	7.730	11.033	3.302
Italy	8.016	8.587	0.571
Japan	19.123	18.633	−0.489
Republic of Korea	32.134	35.602	3.468
Mexico	22.136	21.507	−0.628
Rwanda	7.124	7.559	0.436
United States	22.619	19.494	−3.126
Viet Nam	13.130	41.740	28.610
South Africa	6.239	5.622	−0.617

Viet Nam records the largest increase, at 28.610 percentage points, followed by the Republic of Korea at 3.468 and India at 3.302. France and the United States record the largest declines, at 3.783 and 3.126 percentage points, respectively. The median country change is negative, at 0.489 percentage points below its initial value. This difference between the mean and median identifies the importance of unequal country trajectories.

An exploratory sensitivity calculation excluding Viet Nam changes the mean endpoint difference from an increase of 1.680 percentage points to a decline of 0.243 percentage points. Viet Nam remains in the main

sample. The calculation demonstrates that the direction of the unweighted average depends on one large increase and should not be interpreted as evidence of broadly shared export upgrading.

The 150 annual changes provide a complementary temporal perspective. Their mean is 0.168 percentage points, while the median is 0.046. Positive changes occur in 79 observations and negative changes in 71. Annual changes range from a decline of 10.870 to an increase of 8.348 percentage points. Export composition therefore changes unevenly across both economies and years.

The manufacturing AI estimates cover 2016 to 2018. At the sector aggregate, 2.9 percent of companies report production AI use, comprising 1.5 percent with low use, 1.0 percent with moderate use, and 0.4 percent with high use. A further 0.4 percent report testing without production use, 89.4 percent report no use, and 7.3 percent report that they do not know. Production adoption is therefore limited in the published distribution, with low use accounting for more than half of the reported production adoption share.

Table 2: Production AI use across manufacturing industries with disclosed components

Manufacturing industry	Any Production Use, Percent	Moderate or High Use, Percent
Food	1.7	0.4
Textile, apparel, and leather products	1.4	0.9
Wood products	1.7	0.7
Printing and related support activities	1.9	0.8
Chemicals	3.5	1.8
Plastics and rubber products	2.9	1.1
Nonmetallic mineral products	1.7	0.6
Primary metals	2.0	0.9
Fabricated metal products	3.1	1.5
Machinery	4.8	2.4
Computer and electronic products	4.9	2.4
Electrical equipment, appliances, and components	5.4	3.1
Transportation equipment	4.9	2.1
Furniture and related products	3.1	1.9
Miscellaneous manufacturing	3.2	2.0

Across these 15 industries, production AI use averages 3.080 percent, with a median of 3.100 and a standard deviation of 1.370. Electrical equipment records the highest adoption share at 5.4 percent, compared with 1.4 percent in textile, apparel, and leather products. The difference is 4.0 percentage points. Computer and electronic products, transportation equipment, and machinery also record adoption shares above the industry mean.

Adoption breadth and intensity show related but distinct patterns. Electrical equipment leads both measures, with 3.1 percent reporting moderate or high use. Computer and electronic products and machinery each record 2.4 percent, while transportation equipment records 2.1 percent. Across the disclosed industries, moderate or high use averages 1.507 percent. These comparisons describe reported use categories rather than validated differences in productivity or export performance.

The evidence establishes uneven changes in technology intensive export composition and variation in manufacturing AI adoption. It does not establish a relationship between those patterns because national export observations and industry AI estimates are not matched firm records. Maintaining this distinction accords with evidence that input quality, process productivity, and destination specific pricing represent separate dimensions of manufacturing competitiveness (Hallak & Sivadasan, 2013; Kugler & Verhoogen, 2012; Manova & Zhang, 2012). The supported empirical conclusion is concentrated export restructuring alongside heterogeneous production AI use, rather than a validated effect of AI adoption on export quality.

6. Discussion:

An increase in average export technology intensity can conceal deterioration across most economies. Table 1 reveals this asymmetry: the positive mean change accompanies declines in nine of the 15 economies, while excluding Viet Nam reverses the direction of the average. The analytical contribution is to distinguish concentrated export restructuring from broadly shared upgrading. A rising international average therefore provides an incomplete account of manufacturing transformation. This interpretation complements the emphasis on heterogeneous firms and resource allocation in Bernard et al. (2012), while showing why the distribution of national trajectories matters when interpreting aggregate export indicators. The evidence supports a concentration sensitive reading of structural change rather than a uniform progression toward technology intensive exports.

Production AI adoption also requires interpretation beyond a single adoption rate. Table 2 distinguishes the breadth of reported production use from moderate or high use, revealing differences between technological participation and deployment intensity. Electrical equipment leads both measures, but the ordering of other industries changes when attention shifts toward more intensive use. This distinction gives the adoption categories substantive meaning without treating them as measures of economic returns. Acemoglu and Restrepo (2019) explain technological change through changes in production tasks rather than technology acquisition alone. Viewed through that framework, the observed distributions indicate where production use is reported, while leaving its consequences dependent on the tasks and processes involved. Adoption breadth and intensity should therefore remain separate dimensions of manufacturing transformation.

The composition of reported adoption further qualifies claims about technological maturity. Low use accounts for more than half of the manufacturing sector's production AI adoption share, while Table 2 shows that moderate or high use remains limited even among industries with greater adoption breadth. This is a decomposition of reported use categories, not a decomposition of effects on exports. Its theoretical implication is that access to a technology and intensive deployment represent different organizational states. Cirera and Maloney (2017) emphasize the capabilities required to translate technological opportunities into productive applications. The present evidence gives that distinction a measurable descriptive basis: counting all production users together obscures substantial variation in reported deployment intensity.

International comparison strengthens the case for separating technological adoption, productive performance, and export composition. Table 1 places increasing export technology shares in India, the Republic of Korea, and Viet Nam alongside declines in several advanced economies. Table 2 simultaneously identifies variation in AI use within United States manufacturing. These patterns do not establish that adoption explains national export trajectories. Graetz and Michaels (2018) estimate productivity effects from industrial robots using a different technology measure and research design, illustrating why evidence about automation cannot be transferred directly to AI driven export quality. Fort et al. (2018) likewise demonstrate the importance of distinguishing industries, firms, and establishments when interpreting manufacturing change. The international contribution here is a disciplined comparison across levels, rather than an assumption that technological adoption and export restructuring move together.

The findings change what decision makers should monitor before attributing manufacturing progress to AI. Table 1 supports reporting country distributions and sensitivity to influential trajectories alongside international averages. Table 2 supports separating production use from deployment intensity when assessing technological diffusion. These practices would reveal whether apparent progress reflects broad participation, intensive use, or concentration in a small number of economies and industries. They also redirect research toward matching firm adoption measures with product and destination specific export outcomes. The central contribution is therefore an empirical distinction among export composition, adoption breadth, and adoption intensity. Preserving these distinctions provides a firmer basis for evaluating manufacturing transformation than treating them as interchangeable indicators of technological upgrading.

7. Conclusion and Implications:

Global manufacturing progress can appear widespread even when gains are concentrated and technological deployment remains uneven. This analysis reveals that improving international averages can coexist with declining export technology intensity across most sampled economies. It also distinguishes participation in production AI use from the intensity of that use. The contribution lies in showing how aggregate indicators obscure different dimensions of manufacturing transformation, requiring separate interpretation of structural change and technological deployment. This evidence qualifies approaches that treat technology intensive exports or reported adoption as sufficient indicators of productive upgrading. For managers, the findings support benchmarking deployment intensity alongside participation when assessing technological positioning. Investment reviews should distinguish acquiring technological access from embedding applications within production routines. For policymakers, international comparisons should report the distribution of national trajectories and their sensitivity to concentrated gains before using averages to justify industrial priorities. Statistical agencies can strengthen this assessment by publishing consistent adoption categories and preserving distinctions between limited and intensive use. These practices would improve the information available for resource allocation and reduce the risk of directing support toward apparent progress created by aggregation. Their wider social relevance lies in making industrial development assessments more transparent, supporting clearer scrutiny of investment priorities and public expenditure.

The separate national and industry datasets create an opportunity to develop matched evidence linking technological deployment with exporter outcomes. Future research should combine repeated firm observations with product and destination specific trade records, distinguishing changes in product composition from changes in quality. Broader geographical coverage would permit comparisons across institutional and technological environments. Measures of workforce competence, management practices, and implementation costs could clarify why similar investments produce different outcomes. Designs exploiting credible external changes in

adoption incentives could assess causal relationships. These extensions would connect the descriptive patterns established here to tests of mechanisms, organizational conditions, and transferability.

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