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# Unveiling the global trade network of digital production technologies: a new product classification

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**ABSTRACT**

This research introduces a novel Digital Production Technology Classification (DPTC) based on the Harmonised Commodity Description and Coding System (HS2017) from the World Customs Organisation. The DPTC identifies 120 traded products linked to digital production technologies (DPTs), focusing on technologies that serve as building blocks of digitalised production. The objective is to provide a tool to assess countries' positions in the digitalisation process. Using a step-by-step methodology and expert consultations on production technologies with digital potential, the DPTC distinguishes final products, parts, and instruments, capturing levels of technological complexity. We apply this classification to generate empirical evidence on the global production structure of DPTs by comparing trade networks in 2012 and 2019. The network analysis reveals shifts in global DPT trade structure, countries' roles, and their centrality in production and trade. The classification provides a useful tool for researchers and policymakers to analyse DPT trade networks and inform industrial policy.

**KEYWORDS**

Digitalisation; Digital Production Technology (DPT); product classification; global trade networks; Industrial Policy; Technological Complexity

**JEL CLASSIFICATION**

O14; O33; F14

## 1. Introduction

The development, production, and diffusion of digital production technologies (DPTs) are transforming the nature of industrial production across sectors, reshaping how tasks are performed and how value chains are organised (Ivanov, Dolgui, and Sokolov 2019). These technologies – such as smart robotics, advanced sensors, and networked systems – are central to the broader process of digitalisation, which entails the integration of digital tools and data infrastructures into productive and organisational processes (Ghosh et al. 2022; Lee and Trimi 2021; Szalavetz 2022; Teece and Linden 2017). In manufacturing, in particular, digitalisation refers to the system-level transformation of production activities through digitally enabled tools, data flows, and process integration (Cohen et al. 2019).

DPTs are manufacturing and production-oriented technologies that overlay and augment traditional hardware with smart software, sensors and cyber-physical systems (Andreoni and Anzolin 2019; UNIDO, 2019; Dachs and Wolfmayr 2025). These include, but are not limited to, AI and data analytics, robotics and additive manufacturing, Internet of Things (IoT), cloud computing, and network communication technologies. These technology clusters are increasingly integrated into complex systems of machines, software, and infrastructure, enabling new forms of coordination, monitoring, and control within and across firms (Sturgeon 2021).

Despite their growing importance, systematic tools for measuring the adoption and diffusion of DPTs across countries remain underdeveloped. Existing efforts often rely on three broad types of evidence: industrial surveys, composite readiness indices, and trade-based analyses (Labrunie 2023). Industrial surveys provide a comprehensive overview of digital technologies adoption, yet their sample is often limited to a few firms, sectors and countries (Tortora et al. 2021ONS (2023); Eurostat 2025); composite readiness indices overcome

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This article has been corrected with minor changes. These changes do not impact the academic content of the article.

this limitation being highly comparable, however they tend to conflate multiple dimensions and processes of digitalisation, from services digitalisation to manufacturing, making difficult to understand what is effectively measured (e.g. WEF, UNCTAD and WIPO developed indices, see section 2.2). Our contribution aligns with studies that utilise trade-based indicators, relying on imports of a defined set of products to measure technology adoption and diffusion. Other papers have followed this approach, for example, examining the adoption of robotics (Bonfiglioli et al. 2024) or, more closely related to our approach, analysing a defined set of advanced digital production technologies across 27 European countries (Castellani, Lamperti, and Lavoratori 2022).

We build on and expand the previous work of Castellani, Lamperti, and Lavoratori (2022) in three main directions. First, our methodological approach enables us to create a granular product classification which can be used to study digitalisation in most countries worldwide beyond Europe. Second, our approach does not consider exclusively advanced digital production technologies but also different types of technologies with potential for digitalisation, making it a useful tool to map the diffusion of DPT also in emerging and developing countries. Third, integral to our methodological approach is the deployment of this new product classification in network analysis. Product classifications have been mainly used for benchmarking analysis across countries, much less to identify the network structure underpinning digitalisation processes and diffusion across countries and changes in such structures. Given that DPTs are produced and diffused through complex import-export evolving relationships, network analysis can help unveil structural features of this technology diffusion process and changing balances among countries and regions.

Specifically, we propose a novel Digital Production Technology Classification (DPTC), based on the Harmonised System 2017 (HS2017) product nomenclature, which is used by over 200 countries. Our classification identifies 120 six-digit tradable products that enable the digitalisation of production, selected through a structured, multi-step process combining HS and BEC category filters, keyword searches, and expert validation. These products are organised into three conceptual groups – final capital goods, intermediate components, and digital instrumentation – to reflect their different roles in production systems.

We use our classification to unveil the network structure underpinning the diffusion of DPTs and their evolution over time, conducting a network analysis based on bilateral trade data for 2012 and 2019. Through this analysis, we construct bidirected trade networks to assess countries' positions and roles over time. We also analyse the dynamics of networks for different types of DPTs – that is, final capital goods, intermediate components, and digital instrumentation. This approach captures both the intensity and directionality of trade flows, allowing us to identify central countries and key exporting hubs within the global digital production landscape.

The paper makes three main contributions to the existing academic literature as well as policy debates around digitalisation and technology policy practice. The first contribution is methodological and pertains to the introduction of a new granular product-level classification of digital production technologies, enabling systematic and internationally comparable analysis of countries and the network structure connecting them. The second contribution is about policy practice. Our DTPC tool can provide policymakers with insights into countries' positions, technology diffusion and underpinning structures (trade sources, direction and dependence), ultimately informing the design of policy measures targeting specific technology domains. Third, our empirical analysis provides evidence of the DTP global networks and the changing roles of countries and regions. By doing so, we identify emerging regional dynamics, such as the increasing centrality of East and Southeast Asia and the fragmentation of European networks, with implications for industrial and technological policy.

The remainder of the paper is organised as follows. Section 2 reviews the literature on digital production technologies and measurement approaches. Section 3 outlines the construction of the DPTC and the analytical framework. Section 4 presents descriptive evidence on the global trade network of DPTs. Section 5 discusses evidence from the network analysis, and Section 6 concludes with implications for policy and further research.

## 2. Literature review

### 2.1. Defining digital production technologies within the broader trend of digitalisation

An important conceptual distinction between digitalisation and digital production technologies (DPTs) underlies this paper; the former indicates a systemic transformation, while the latter refers to the concrete technological artefacts that enable this transformation. Digitalisation is a broad phenomenon that encompasses shifts in organisational models, production structures, and information flows. When applied to the manufacturing sector, digitalisation indicates the establishment of networks between machines and the use of software systems and data analytics for monitoring, controlling and optimising interconnected work processes (Hirsch-Kreinsen and Hompel 2017). Part of this process, DPTs refer specifically to physical goods, such as machinery, instruments, and components, that support digital operations on the factory floor through connectivity. Connectivity is key as it brings the two concepts (digitalisation and DPT) together and is the real source of value creation mechanisms for businesses (Cirillo et al., 2021; De Propris and Bailey 2021).

We place this study in the DPT literature and emphasise production because mapping DPTs reveals the capabilities, emerging and established, that support structural transformation. Production technologies, in particular, spur industrial development through their pivotal contribution to the accumulation of capabilities (Amsden 1990; Andreoni and Chang 2019; Lall 1992). Production technologies historically include a wide range of equipment, from conventional machine tools to programmable devices. With digitalisation, these technologies evolve through sensorisation, software integration, and network connectivity, enabling real-time data exchange, remote monitoring, and autonomous control. In this context, DPTs are not defined solely by automation or numerical control, but by their capacity to operate as part of interconnected, data-intensive production systems (Andreoni and Anzolin 2019; Tassey 2014).

The digital transformation of production relies on multiple layers of enabling technologies (e.g. Jia et al. 2019). These include, for example, (i) sensors and measurement devices that collect and process data, (ii) communication infrastructure for data transmission, (iii) computational tools for data processing and storage, and (iv) interfaces and actuators for feedback and control. Together, these technologies constitute the infrastructure of industrial digitalisation and are increasingly embedded in international trade.

### 2.2. Industrial digitalisation and empirical approaches

The digitalisation of production systems is a central feature of contemporary industrial transformation. This process involves not only the introduction of new digital tools but also the reconfiguration of productive and organisational capabilities across firms and sectors (Andreoni, Chang, and Labrunie 2021; Szalavetz 2022; Teece and Linden 2017). As digitalisation gains strategic relevance in shaping competitiveness and resilience, there is increasing demand for metrics and indicators that can capture its scope, diffusion, and structural implications.

Several empirical strategies have been deployed to measure both the broader concept of digitalisation (see section 2.1) and of digital production technologies at the country or sector level. These can be grouped into three main approaches: industrial surveys, composite readiness indices, and trade-based analyses.

Industrial surveys typically provide firm-level data on the adoption of digital technologies and associated organisational practices. While such surveys offer detailed insights, they are often limited in geographic scope and lack international comparability due to differences in design and definitions. Notable examples include the European Manufacturing Survey (Albrieu et al. 2019), the European Investment Bank's EIBIS dataset, and national studies for countries such as South Korea and Germany (Sommer 2015). In emerging economies, surveys have been conducted in Brazil (Ferraz et al. 2020), Vietnam, Ghana, and others, often under the auspices of international organisations (UNIDO, 2019; UNDP, 2020). Despite their value, these studies remain fragmented and often rely on self-reported indicators of digital capability.

A second strand of research relies on composite indices, a great part of which is an attempt to measure 'digital readiness'. These indices combine secondary data on infrastructure, skills, innovation, and regulation. While useful for cross-country benchmarking, they often conflate inputs, enablers, and outcomes, and may obscure underlying technological heterogeneity. The use of multiple proxies and arbitrarily weighted components can limit their interpretability and relevance for understanding specific technologies or industrial dynamics. For instance, the European Commission's Digital Economy and Society Index (DESI) merges connectivity, human capital, use of digital services, firm adoption, and digital public services, mixing enablers with firm- and citizen-level outcomes in a single score. Similarly, the World Bank's Digital Adoption Index (DAI) aggregates adoption by people, businesses, and governments from heterogeneous proxies (e.g. broadband/mobile penetration, firm web presence, online public services), which makes it hard to isolate specific technological capabilities or bottlenecks.

A final approach is the one based on trade-based data analysis. Using trade data to map capabilities of various types has been a common approach in economics; the most famous example is Hidalgo and Hausmann's (2009) analysis of the so-called product space and derived economic complexity of different countries. By tracking the flows of digital goods across borders, these methods use trade data to extract synthetic measures of the degree of digitalisation of specific countries. Macedo et al. (2020), for instance, analyse revealed comparative advantages in capital and Industry 4.0-related goods, linking them to robot intensity and employment risk indicators. Another recent contribution from Bonfiglioli et al. (2024) uses robot imports to study firm-level outcomes. The product lists used in such studies are often narrow (e.g. focusing on a single technology) and not derived from systematic classification procedures, which limits their comprehensiveness and comparability. A systematic attempt is found in Castellani, Lamperti, and Lavoratori (2022), who develop a classification of three sets of Industry 4.0-related products based on the EU Combined Nomenclature (CN8). While this approach improves precision at the product level, it is constrained by its regional scope and a narrower technological focus on advanced digital production technologies (i.e. advanced industrial robots, additive manufacturing, and the industrial Internet of Things), making it less applicable to studying the structural change in emerging economies in this context. Most developing countries lack access to advanced digital production technologies, yet in these countries several production activities – from agriculture to manufacturing and logistics – can be digitalised, that is, they have the potential for digitalisation through production system retrofitting and technology integration processes. In fact, in several cases, it is by turning this digital potential into reality that countries across the global south move their first steps into digitalisation and develop their digital technological capabilities (Figuereido and Zahra 2025).

## 3. Methodology and rationale to build the DPT classification

This section presents the methodology used to construct the Digital Production Technology Classification (DPTC); our framework builds on the classification of internationally traded goods to identify a consistent set of digital production technologies.

### 3.1. Conceptual framework for our DPT classification

We developed the classification of Digital Production Technologies through a multi-step process that combines product-level trade data with both conceptual and empirical criteria. The goal was to identify a set of tradable goods that play a central role in enabling production digitalisation. Unlike an analysis focused on a specific set of advanced digital production technologies such as robots (Castellani, Lamperti, and Lavoratori 2022), we aim to broaden the scope of our classification to include technologies that have the 'potential' to digitalise the production process. Tradable goods with a 'digital potential' are those technological products constituting the 'building blocks' of digitalised production processes such as screens, antennas or routers, microelectronic components, and machinery with digital capabilities and interface. The integration of these technological products into other production technology and systems have the potential of enabling their digital transformation. This integration often involves various degrees of technological retrofitting – e.g. from the simple sensorisation of a production technology requiring sensors, actuators and screen interfaces – to most advanced forms of integration which may result in indigenous innovation in products, processes and services (Andreoni and Anzolin 2025). There are various examples across sectors, from the introduction of precision feeding in farming (through the integration of sensors, antennas, routers, etc. that enable data analytics underpinning feeding optimisation) to more complex forms of retrofitting of a robotic cell centred around an ADPT being a robotic arm (but further enabled by various human interface systems such as screens for enhanced automation flexibility and human control).

In our conceptual framework, we distinguish three categories of products that can be understood as having digital potential: *parts and components* of digital products, such as electronic circuits, memories, processors, antennas, etc. (the bottom layer of the pyramid in Figure 1); *intermediate products*, such as sensors, actuators, connectivity and network devices, etc. (the middle layer in Figure 1), which make use of

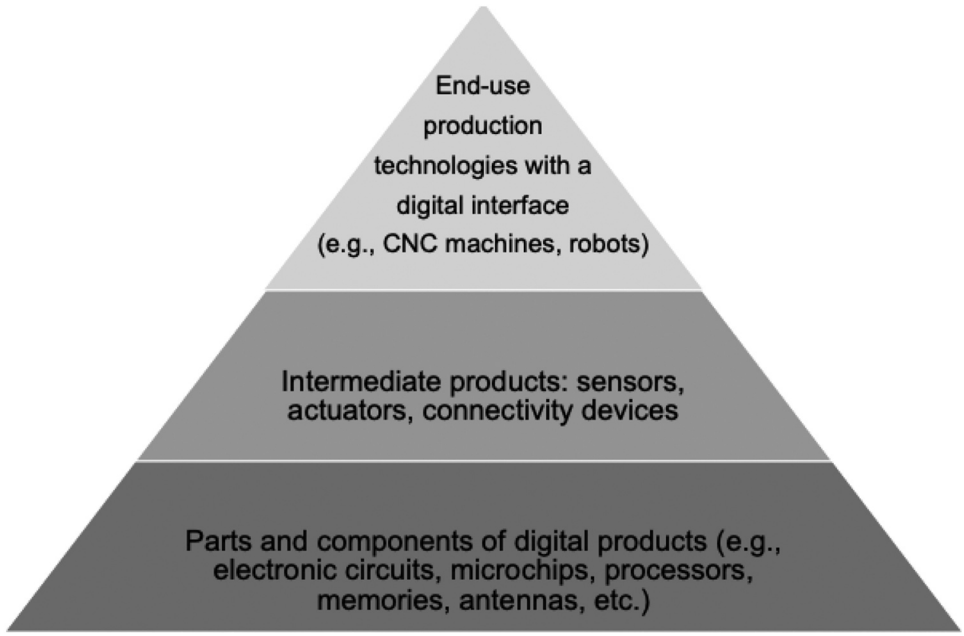


**Figure 1.** Conceptual framework. Source: Authors.

the digital parts and components and that can be both a final and an intermediate product depending on their use; and *end-use production technologies with a digital interface* – these make use of both the digital parts and components and of intermediary products to enable its integration to digitalised production processes (top layer in Figure 1). These three categories of products play key functions in the digitalisation of production processes and systems.

It is essential to examine technologies with digital potential to uncover the various technology layers and technology types that enable digitalisation of production systems. We zoom into a couple of examples which pertain to key technologies depicted in Figure 1.

First, sensors are one of the critical technologies for data collection and management, enabling the creation of various data streams that can be unified within business systems within firms. For example, they allow the connection of Manufacturing Execution System, Enterprise Resource Planning, and other database management systems, thus enabling data transmission across production flows (Colombari et al. 2023). Our classification provides special attention to various types of sensors, including thermostats, scales, cameras, and accelerometers (also known as vibration sensors). In addition, sensors are critical in many 'infra-technologies' and instrumentation for control engineering (Tassey 2014), used in the processes of technology scaling-up, monitoring and testing. Finally, sensors are also an important component of advanced manufacturing and infrastructures (PCAST, 2011), allowing the generation of data transmitted through devices such as antennas, gateways, routers, and other wired or wireless connectivity devices.

Second, actuators are another key part of the digitalisation process. Once collected the data is analysed and then returned to the shopfloor (or, in many cases, has never left) and can either provide insights for decision-making by humans or generate autonomous responses, such as closing a valve, moving a lever, activating a cooling system, opening a hatch or window, ordering a spare part, etc. – all without human interference, and through devices named actuators. Third, in every step of the process, data must be displayed for setting up, monitoring, tracking, and maintenance purposes. There is indeed a plethora of hardware interfaces without which data and related analytics could not be monitored and processed by human operators and productive organisations in decision-making processes. These hardware interfaces are often integrated into data-enabled machines and devices.

Examining trade data with this conceptual framework in mind can give more detailed indications about a country's level of digital capabilities and production organisation, such as whether it is specialised in intermediate goods or final goods, or the most sophisticated instrument technologies (see step 3 in

Section 3.2). Building on the granularity of UN Comtrade data, we used BEC[1] classification to intersect product categories in a way that allows us to distinguish between final products, parts and instruments (see section 3.2).

### 3.2. Step-by-step construction of the DPTC

In this section, we present the different methodological steps we followed to build our classification.

#### 3.2.1. Step 1: data selection and levels of product classification

We extract trade data at the six-digit level to classify products as DPTs. While there are some caveats to using trade data, it remains the most reliable data source, with granular data available for most countries. The main caveat is that trade data does not capture products produced and consumed in the domestic economy. Hence, it has a bias, especially for those economies with a large internal market and domestic-oriented manufacturers of digital technologies (e.g. Brazil). We use data from the Harmonised Commodity Description and Coding System (HS2017) of the World Customs Organisation, which employs a classification of products at the 6-digit level. We focus on trade in goods; service trade, although increasingly relevant in digitalisation,[2] is excluded due to its limited coverage in HS-based classifications. The classification we built is available from 2012 to 2019, with the possibility to convert product codes to 2022.

#### 3.2.2. Step 2: selection of the most suitable product classification

Next, we employ the Harmonised System (HS) 2017 for product classification. This choice is particularly relevant for our study because HS 2017 includes new codes specifically designed to categorise products based on their digital attributes. For instance, it provides distinct codes for machines based on their internet connectivity capabilities, differentiating between those that can connect to the internet and those that cannot. This level of detail in product classification allows for a more accurate and nuanced identification of digital production technologies. 2012 is the earliest year we could align with HS2017 categories, and 2019 is the most recent pre-pandemic year.

#### 3.2.3. Step 3: identification of the relevant HS chapters and BECs filtering criteria

To identify DPTs (i.e. capital goods, parts, and instrumentation), we narrowed our research to specific product categories described in section 3.1 within the HS 2017 classification. We selected the following chapters, given our focus on production technologies:

- HS 2017 Chapter 84 includes machinery and mechanical appliances and their parts.
- HS 2017 Chapter 85 includes electrical machinery and equipment, sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles.
- HS 2017 Chapter 90 covers optical, photographic, cinematographic, measuring, checking, precision instruments and apparatus, along with their parts and accessories.

Additionally, to ensure our analysis remains focused on machinery and appliances used in digital manufacturing production and excludes those intended for consumer use, we filtered these three HS chapters using BEC 4 classification:

- BEC 4 Chapter 41 focuses on capital goods, excluding transport equipment.
- BEC 4 Chapter 42 covers parts and accessories.
- BEC 4 Chapter 22 includes industrial supplies not specified elsewhere and that have been processed.

[1]The Broad Economic Categories (BEC) classification is a UN-developed system that groups traded goods according to their main end-use (intermediate goods, capital goods, and consumption goods), linking trade data with national accounts and demand-side analysis. By mapping products from systems like the HS, as in our case, into functional use categories, BEC enables consistent international comparisons of trade flows.

[2]Increasingly higher value-added segments of production are the knowledge-intensive services such as software development and implementation, R&D, design, marketing, and post-sale activities.

We conducted the filtering using the correspondence table between HS2017 and BEC 4, which is publicly available. While the correspondence methodology document highlights that there are 'many-to-one' cases from HS to BEC, we followed the UNDP methodology, which assigns the HS 2017 code to the correlate that accounts for 75 % or more of the total trade in all the correlates.[3] By applying these filtering criteria to our products clustered under HS 84, 85 and 90, we narrowed the list to 818 products.

#### 3.2.4. Step 4: systematic identification of DPTs through keyword selection and product analysis

As a final step, we distinguish those clearly identifiable as digital production technologies – based on 'self-explanatory description' and related keywords. We tested multiple keywords and assessed their outcomes. We interrogated the data set by reiterating the keyword identification process until saturation (when we could not find any further products). The selected keywords for which we could find correspondence in the 'self-explanatory description' were: (E)lectronic, (D)ata, (N)umerical, (N)etwork, (A)utomatic, (T)ransistor, (S)emiconductor, (I)nstruments, (A)pparatus, (W)afers, (C)alcul-, (C)ontrol, (T)esting, (M)eter, (R)emote, (-)stats, (R)adio, (W)eigh.[4]

Implementing the filters mentioned earlier streamlined our dataset, narrowing the product count from the original 818 to 262 products. To ensure accuracy and reliability, we reviewed the remaining products individually. Products not directly related to digitalisation were excluded from the classification.[5] This step-by-step methodology was reviewed by two experts with engineering backgrounds to ensure it is accurate and consistent; we made adjustments and refined our procedure as part of this iterative process. The adjustments we made after discussing with the experts are like the following: (i) we excluded the category of telephones for cellular network (wireless) and their parts (851712 and 85,170), because although they can also be used in production facilities to monitor and program, the vast majority is not production related[6]; (ii) we excluded also a category whose description indicates that it was mostly related to light-emitting diodes (LED), they had been included because of photosensitive *semiconductor* devices (854140) but are likely to be mostly LED and thus not directly related to production technologies. Finally, (iii) we excluded the category of printing machines (844331) because of their scarce digital potential and parts of diodes and transistors (854190), because they are parts with electric functions that are too basic and are likely to be used in areas broader than production digitalisation.

We ended up with a final list of 120 DPT products (see list in Appendix I – supplementary material). Alongside each product, Appendix I provides the rationale behind its inclusion, offering insights into the factors that determine its relevance to digitalisation within our study. Figure 2 summarises the steps taken in refining our product list, from the initial application of filters to the final manual check and selection of products.

To make the best use of our classification as a policy and analytical tool where digital capabilities (and their different levels of intensity) can be mapped across countries we have classified each product under one of these categories: (1) final goods and (2) parts and components (matching HS codes 84 and 85 with BEC 21 and 22 as reported in section 3.2 *step 3*), and (3) instruments, which include all HS 90. Considering final products and parts allows us to map products at different layers of our pyramid (see Figure 3); for example, if we take sensors, they will mostly be in the second layer of our pyramid, and the related parts necessary to produce it will mostly be in the bottom layer. The first layer would include products such as CNC machines and robots, where sensors are often inserted, and which are end-use technologies with a digital interface. We keep instruments as a separate category since this type of technology is a critical and more sophisticated category for the development of digital production technologies, and it embeds higher technological capabilities.

[3]urihttps://unstats.un.org/unsd/classifications/Econuri/corr-notes/HS2017%20conversion%20to%20earlier%20HS%20versions%20and%20other%20classifications.pdf

[4]Other keywords were tried but excluded as their results were either void, redundant, or misleading. These included: wireless, artificial, computer, automated, sensors, printer, digital, chips, conductor, additive, internet.

[5]Some products had the key words but not with the intended meaning. For example, many products had the word 'numerical' in the expression 'not numerically controlled', thus being exactly the opposite of what we were trying to capture. Another example: Product code 844,711 'Circular knitting machines, with cylinder diameter ≤ 165 mm' has the word 'meter' within 'diameter' which is completely unrelated to what we wanted to capture with the keyword 'meter' – aimed at thermometers, electrical current metres, and other sensors. Also, all medical devices were excluded from the analysis.

[6]This was a very numerous category, and our network analysis is robust to its exclusion.

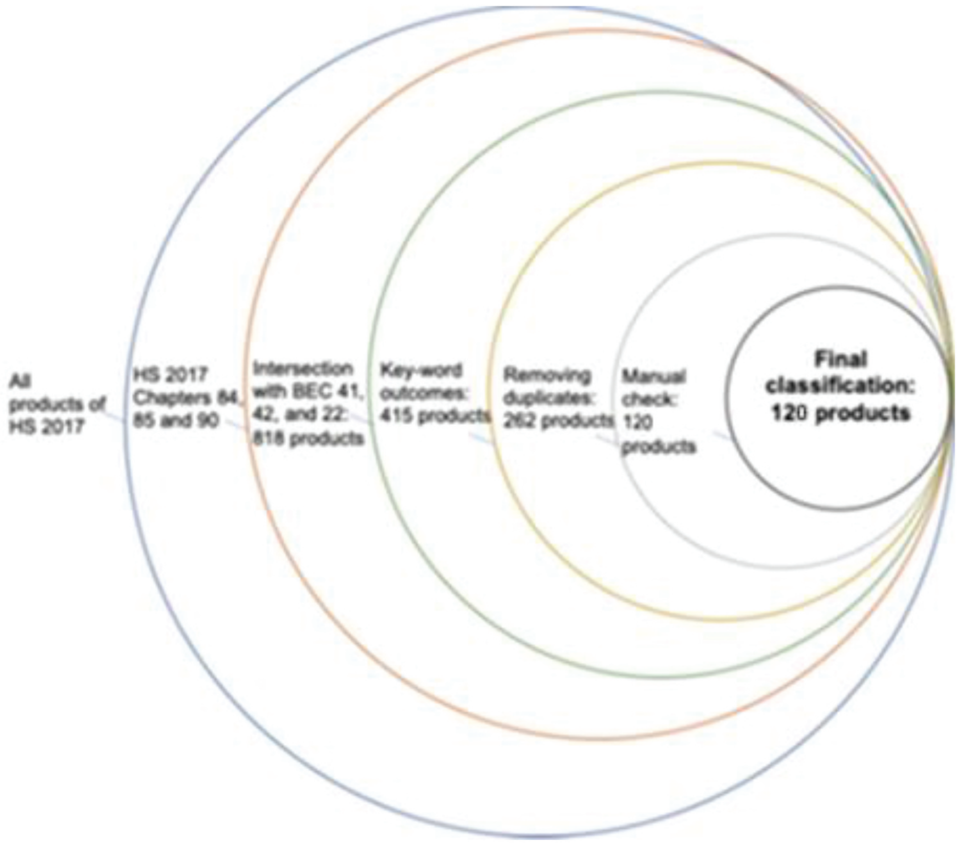


**Figure 2.** Summary of the methodological steps to build the DPT classification. Source: Authors.

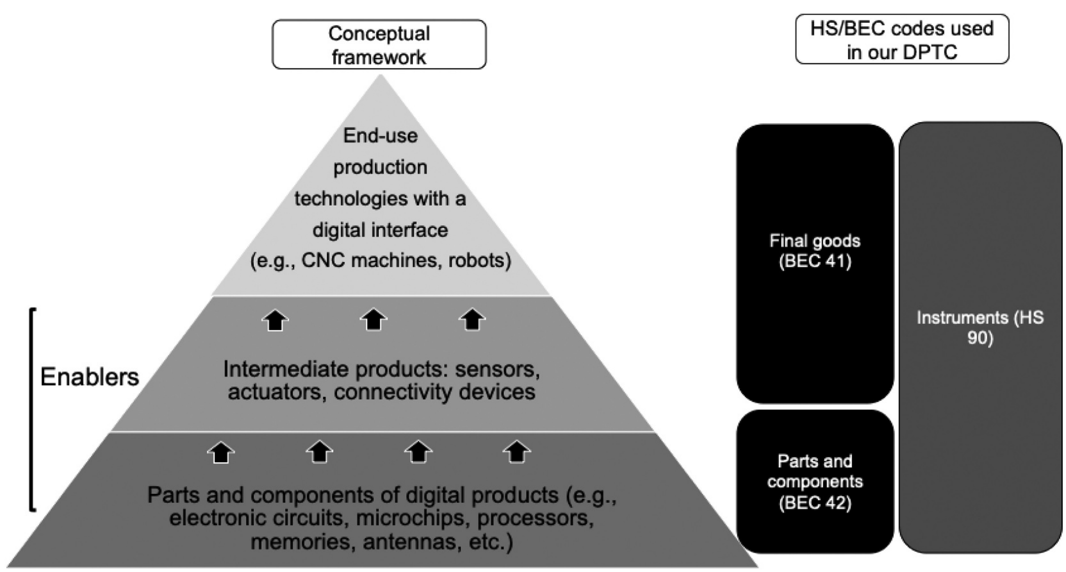


**Figure 3.** Conceptual framework and categories of our DPTC. Source: Authors.

## 4. Network results and analysis

To construct the Digital Production Technologies (DPT) trade network, we used bilateral trade data from the United Nations Comtrade Database (UNCD), accessed through the World Bank's World Integrated Trade Solution (WITS) interface. We filtered the data for 120 identified DPT products at the six-digit HS level for the years 2012 and 2019. These years were selected to provide a meaningful time span for structural comparison while avoiding the distortions caused by the COVID-19 pandemic. Classification consistency was ensured by aligning 2012 data (originally in HS2012) with the HS2017 nomenclature used in 2019, following concordance tables provided by the UN Statistics Division.[7]

A descriptive analysis of DPT and total trade flows provided preliminary insights into the structure and evolution of global DPT trade. Building on this, we apply a network analysis to study the evolution of the DPT trade network, which allows us to address two key research questions: What are the structural characteristics of the global trade network in digital production technologies? And how have these structures evolved between 2012 and 2019?

### 4.1. Network structure of global digital trade (2012–2019)

The international trade network for digital products is extensive, highly connected, and has become significantly more integrated between 2012 and 2019.

Table 1 summarises key network metrics for all digital products and for the three sub-networks: final digital goods, parts and components of digital products, and digital technology instruments, in 2012 and 2019. Nearly all countries participate in digital trade. In all digital products, over 252,000 distinct bilateral product trade links were active in 2012, increasing by one-third to over 336,000 by 2019, reflecting a significant expansion in the number of trade connections.

Figure 4 provides a visual representation of the global Digital Production Technologies (DPT) trade network for 2012 and 2019. The network graphs illustrate the main trade connections between countries, highlighting the most significant flows and the overall topology of the system. Nodes represent countries and links correspond to bilateral trade relationships in DPT products, allowing us to visualise the central hubs and the density of connections within the network. The visualisation complements the quantitative metrics reported in Table 1 by providing an intuitive overview of how trade relationships are organised and how the network structure evolved over time.

Between 2012 and 2019, DPT trade networks became markedly more connected, reciprocal, and integrated (We can see that in Table 1 and Figure 4). The number of bilateral trade links and network density rose significantly, indicating that countries traded larger volumes and a wider variety of digital products with more partners. Reciprocity also increased modestly overall, more significantly in parts and components, suggesting the fact that once trade-flows are established they can transform into potential supply-chain linkages. Although degree assortativity remained negative (around −0.4), it became slightly less so, implying a mild reduction in the core – periphery divide as leading economies traded more among themselves. Clustering was consistently high and continued to increase (global transitivity rose from 0.58 to 0.65), reflecting denser regional and triadic connections that were reinforced by integrated production networks.

**Table 1.** Global network metrics for digital product trade networks,[8] 2012 vs. 2019.

| Network | Year | Nodes | Links (count) | Reciprocity | Assortativity | Clustering (global) | Clustering (avg. local) | Largest SCC | Modularity |
|---|---|---|---|---|---|---|---|---|---|
| All DPT | 2012 | 242 | 252,375 | 37.1% | −0.482 | 0.580 | 0.845 | 101 | 0.184 |
| | 2019 | 243 | 336,589 | 38.8% | −0.390 | 0.654 | 0.833 | 131 | 0.157 |
| Final DPT | 2012 | 239 | 70,875 | 34.7% | −0.446 | 0.586 | 0.838 | 101 | 0.182 |
| | 2019 | 239 | 100,195 | 35.5% | −0.355 | 0.637 | 0.822 | 131 | 0.178 |
| Parts DPT | 2012 | 242 | 57,797 | 37.9% | −0.474 | 0.565 | 0.845 | 101 | 0.129 |
| | 2019 | 241 | 69,652 | 41.4% | −0.407 | 0.612 | 0.827 | 131 | 0.103 |
| Instruments | 2012 | 239 | 123,651 | 36.4% | −0.440 | 0.600 | 0.853 | 101 | 0.253 |
| | 2019 | 240 | 166,459 | 38.0% | −0.379 | 0.650 | 0.835 | 131 | 0.202 |

Source: United Nations Comtrade Database. Table: Authors.

[7]Conversion table is available in the following link: https://unstats.un.org/unsd/classifications/Econ

[8]Each network is directed (i.e. exports and imports) and weighted by trade value. 'Links' represents the total number of distinct bilateral trade relationships (at the product level) observed. 'Reciprocity' refers to the number of country pairs that engage in mutual trade. 'Assortativity' is the degree of correlation (negative values indicate a hub-and-spoke structure). 'Clustering (global)' is the global transitivity (fraction of closed triads), while 'Clustering (avg. local)' is the average of individual countries' clustering coefficients. 'Largest SCC' is the size of the largest strongly-connected component (i.e. number of countries in the largest group of mutually reachable countries), and 'Modularity' is the Louvain community modularity score (with three communities identified in each case).

Network cohesion increased, as the largest strongly connected component expanded from 101 to 131 countries, while smaller components declined, indicating that more nations became mutual traders within the global digital trade core. Community detection reveals three main clusters in both years; however, modularity decreased, indicating weaker regional segmentation and increased cross-community exchange. Overall, the DPT trade has evolved towards denser, more balanced, and globally interconnected structures, with a growing number of economies actively participating in two-way digital trade.

Despite lower modularity, three main trade communities remain economically and geographically interpretable. In 2012, clusters corresponded broadly to (1) Europe – Africa – Middle East, (2) East Asia and emerging economies, and (3) the Americas – Pacific.[9] By 2019, these blocs had persisted but had become more fluid: India had shifted from the Europe-centred to the Asia-centred cluster, reflecting deeper integration with East Asian supply chains, while Brazil's position varied by product type, being linked to Asia in component trade but to the Americas in final goods. Such shifts illustrate the growing interconnection among regional blocs, consistent with the decline of modularity and the strengthening of cross-regional trade linkages.

In the aggregate digital products network, global trade is highly concentrated among a few dominant hubs.

While several of our descriptive patterns, such as China's prominence or the persistence of a core – periphery configuration, may appear consistent with standard trade indicators (e.g. market shares, concentration ratios, or top-exporter rankings), the network perspective adds distinct insights that those metrics cannot recover. First, network measures capture the structure of interdependence: directionality and reciprocity reveal whether countries are mutually embedded in multi-stage value chains or remain in one-way importer positions, which is directly relevant for assessing dependency and upgrading potential. Second, centrality metrics (especially betweenness) identify systemic 'connectors' and choke points, countries that intermediate trade paths across otherwise weakly connected partners, highlighting vulnerabilities and propagation channels for shocks that are not visible in aggregate shares. Third, clustering, assortativity, and community structure reveal regional production blocs and cross-bloc bridging, allowing policy-relevant interpretation of supplier diversification, supply network resilience, and where strategic interventions (e.g. supplier development, standards participation, or regional partnerships) may reduce exposure and facilitate capability building.

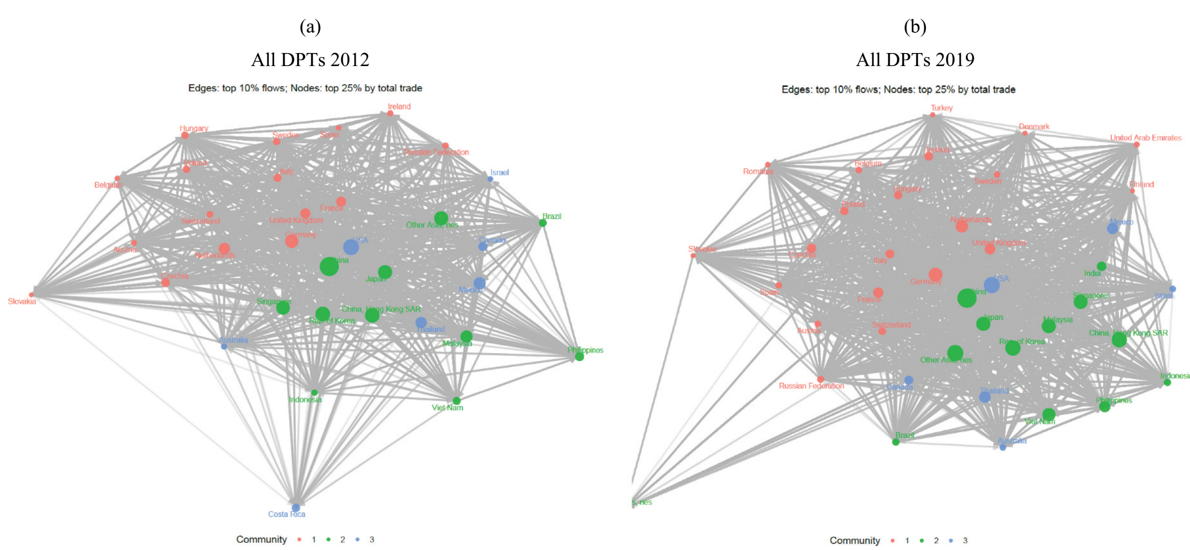


**Figure 4a.** Network visualisations of digital production technology trade (top flows and major trade links).

[9]The complete data can be found in the supplementary material.

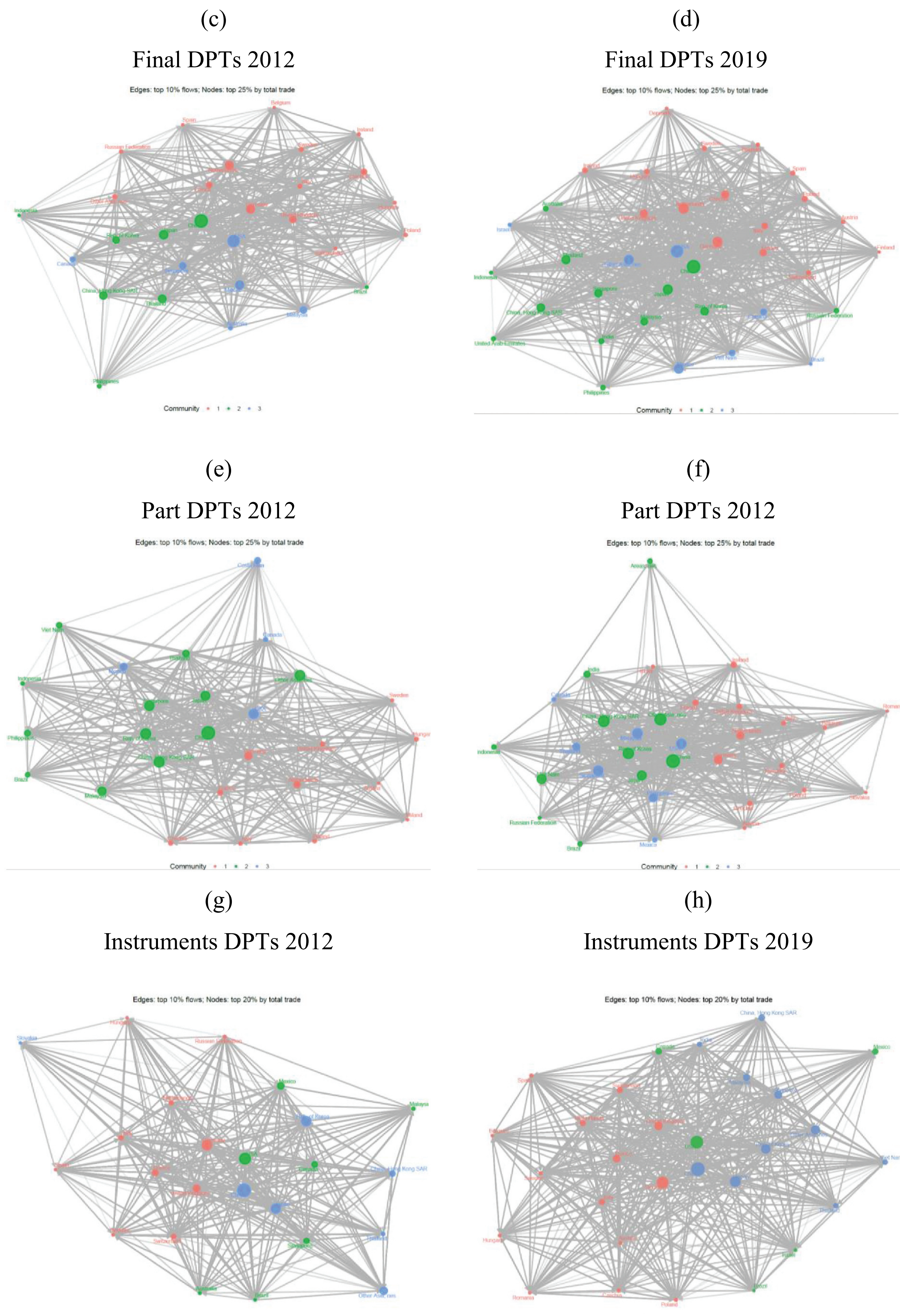


**Figure 4b.** Network visualisations of digital production technology trade (top flows and major trade links) by digitalisation breakdown.

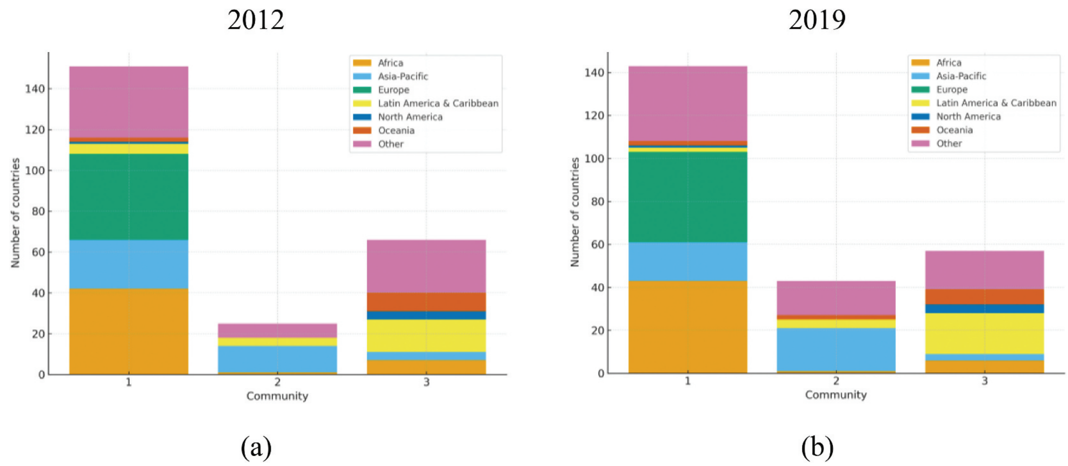


**Figure 5.** Community membership by region, 2012 and 2019, all DPTs. Source: United Nations Comtrade Database. Figure: Authors. Note: Community detection identifies clusters of countries that are more densely connected within the DPT trade network than with the rest of the system. Figure 5 shows the regional composition of these clusters. Community 1 forms the largest and most globally diversified group, representing the core of the global DPT trade network. Community 2 is smaller and more regionally concentrated, mainly including countries with more limited connectivity and more peripheral participation. Community 3 occupies an intermediate position, linking several emerging and advanced economies and reflecting cross-regional supply-chain connections. Together, these communities capture the main structural blocs of the network and illustrate how digital production trade remains organised around partially overlapping regional production systems.

Against this backdrop, Table 2 reports node-level centrality measures that allow us to move beyond aggregate trade shares and identify countries' structural positions – whether as hubs, intermediaries, or peripheral actors – within the global DPT trade network.

Network centrality measures indicate that China is the dominant hub. In 2012, China already had the maximum degree (it traded digital products with virtually every other country), and by 2019, China's connectedness only increased. The betweenness centrality of China quadrupled from 2012 to 2019 – meaning that an overwhelming share of the shortest trade paths between other countries go through China. By 2019, its weighted betweenness was by far the highest of any country, indicating China is the key intermediary linking global trade routes. This suggests that many countries that do not trade directly rely on China as a standard connection (for instance, China might import components from one country and export finished goods to another, effectively connecting those countries' trade indirectly). The United States, Netherlands, and Singapore also show high betweenness, reflecting their roles as major global trans-shipment or logistics hubs (the Netherlands for Europe, Singapore and HK for Asia, the USA for the Americas). However, by 2019, no country rivals China on this measure, highlighting a single-hub-dominated network.

Despite China's dominance, the all-digital network is not a single-star network; rather, it comprises a diverse group of major traders. The United States remains a central node (the only other country, besides China, with both export and import volumes above $200 billion). The EU countries, taken together, form another pillar of the network – for example, Germany (exports $79 billion, imports $25 billion in 2019) and the Netherlands (exports $57 billion, imports $28 billion) act as leading exporters and entry points into the European market. The UK, France, Italy, and other EU states also contribute significantly, though individually they rank below the top Asian economies. East Asian economies, such as those of South Korea, Japan, Taiwan, and Singapore, also occupy positions among the top 10–15 nodes. In Southeast Asia, as mentioned, Vietnam and Malaysia had risen sharply by 2019, integrating into the core. Meanwhile, many developing countries in regions such as Africa and South America remain more peripheral; they appear in the network primarily as importers of digital goods and have fewer connections and smaller trade volumes. This unequal distribution of connectivity is evident in the heavy right tail of the trade network, where the degree and strength distributions follow a power-law pattern. As a result, a small percentage of countries account for the majority of connections and volume. In fact, we find that in 2019 the top 10 exporting

**Table 2.** Node-level characteristics of major countries in the DPT trade network, 2012–2019.

| Country | In-degree 2012 | In-degree 2019 | Δ In-deg | Out-degree 2012 | Out-degree 2019 | Δ Out-deg | In-strength 2012 | In-strength 2019 | Δ In-str | Out-strength 2012 | Out-strength 2019 | Δ Out-str | Betw 2012 | Betw 2019 | Δ Betw |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| China | 9041 | 12988 | +3947 | 4728 | 5254 | +526 | 368.6 | 487.7 | +119.1 | 393.4 | 513.3 | +119.9 | 0.34 | 1.41 | +1.06 |
| Taiwan | 6544 | 8035 | +1491 | 0 | 3669 | +3669 | 157.3 | 271.4 | +114.1 | 0.0 | 94.7 | +94.7 | 0.00 | 0.39 | +0.39 |
| Hong Kong | 4876 | 6574 | +1698 | 2502 | 2743 | +241 | 7.4 | 17.4 | +10.0 | 172.5 | 248.6 | +76.1 | 0.06 | 0.09 | +0.02 |
| USA | 8602 | 11388 | +2786 | 5533 | 6025 | +492 | 109.3 | 129.8 | +20.4 | 167.0 | 218.4 | +51.5 | 0.10 | 0.20 | +0.10 |
| Malaysia | 4689 | 5950 | +1261 | 0 | 3668 | +3668 | 90.4 | 125.9 | +35.6 | 0.0 | 45.1 | +45.1 | 0.00 | 0.06 | +0.06 |
| Viet Nam | 1819 | 3657 | +1838 | 2831 | 3146 | +315 | 8.1 | 67.7 | +59.6 | 15.0 | 58.5 | +43.5 | 0.00 | 0.01 | +0.00 |
| India | 4853 | 7221 | +2368 | 0 | 4320 | +4320 | 2.7 | 3.0 | +0.3 | 0.0 | 31.8 | +31.8 | 0.00 | 0.01 | +0.01 |
| Rep.Korea | 5884 | 7274 | +1390 | 4055 | 4553 | +498 | 135.0 | 183.0 | +48.0 | 56.6 | 82.6 | +26.1 | 0.16 | 0.07 | −0.09 |
| Philippines | 2908 | 3650 | +742 | 0 | 3279 | +3279 | 32.2 | 42.9 | +10.8 | 0.0 | 21.6 | +21.6 | 0.00 | 0.00 | +0.00 |
| Germany | 8454 | 11097 | +2643 | 6338 | 6735 | +397 | 61.4 | 78.1 | +16.6 | 57.5 | 79.1 | **+21.6** | 0.05 | 0.06 | +0.01 |

Source: United Nations Comtrade Database. Table: Authors. Note: The DPT trade network is directed and weighted: links go from exporter to importer, and weights correspond to bilateral trade values (US$). In-degree (imports) is the number of incoming trade links a country receives (i.e. the count of distinct exporter–product relationships reaching the country); out-degree (exports) is the number of outgoing trade links a country sends (i.e. the count of importer–product relationships served by the country). In-strength and out-strength are the corresponding total values of imports and exports (sum of incoming/outgoing link weights), reported in billions of current US dollars. Betweenness centrality (Betw) captures a country's brokerage position in the trade network: higher values indicate that the country lies on a larger share of the network's shortest trade paths and therefore intermediates trade connectivity. Δ reports the change between 2019 and 2012.

countries accounted for roughly 75% of total digital exports, and the single most significant bilateral trade link (likely China – Hong Kong or China – USA) alone represents a substantial share of world trade.

In terms of communities, the all-digital network's three community structure persist. China and most of East Asia are firmly in the Asia-Pacific community; the US anchors the Americas community; and Germany, along with other EU economies, anchors the Europe-centric community. However, by 2019, the distinctions among these blocs blur: for example, Mexico (a NAFTA member) trades so extensively with the US that it's in the Americas cluster for all products, but Mexico also has growing linkages with Asia (in parts trade). Russia and India are interesting cases – Russia remains part of Europe's cluster (due to historical trade ties between Europe and Asia for Russia). In contrast, India, as noted, shifted to Asia's cluster by 2019, reflecting shifts in policy and supply chain. Overall, the all-digital network can be described as highly globalised yet with regional substructures. The period 2012–2019 saw Asia's substructure strengthening its prominence within the global web, while all substructures became more interlinked (hence decreasing modularity).

### 4.2. *Final digital goods network*

The final digital goods network focuses on trade in finished digital products (such as completed electronics, consumer ICT products, etc.). This network exhibits some crucial differences from the all-digital aggregate, particularly in the balance between advanced and emerging economies.

The network characteristics of the final goods trade (see Table 3) reflect a more fragmented structure. Many countries either export or import final goods, but not both, leading to the lowest reciprocity. Several developing countries import consumer electronics but do not export them. The strong components of the final goods network were smaller in 2012, with only 101 countries in the most significant SCC, meaning a large number of nations were exclusively final-good importers. By 2019, the largest SCC expanded to 131 (like the others), implying more countries that previously only imported final goods (or only exported) have started to both import and export some final products (possibly assembly or re-export activities).

Community-wise, the Americas cluster is quite prominent because the US and much of Latin America form a tightly knit trade group for finished products (largely due to supply chains). Europe remains its own cluster, and Asia (with China and regional partners) another. Interesting differences: Brazil is grouped with the Americas cluster in final goods (because Brazil imports a significant amount from the US/EU, and relatively less from China, compared to other flows). India remains aligned with Asia (as a significant importer from China). The modularity of the final goods network is slightly higher than that of parts, indicating more regionalisation – for example, many final products sold in Europe are made in Europe, and similarly for the Americas, reflecting possibly higher trade barriers or consumer preferences that keep final goods trade somewhat more regional.

**Table 3.** Node-level characteristics of major countries for final digital goods, 2012–2019.

| Country | In-deg 2012 | In-deg 2019 | Δ In | Out-deg 2012 | Out-deg 2019 | Δ Out | In-str 2012 | In-str 2019 | Δ In-str | Out-str 2012 | Out-str 2019 | Δ Out-str | Betw 2012 | Betw 2019 | ΔBetw |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| USA | 2484 | 3585 | +1101 | 1600 | 1827 | +227 | 29.9 | 32.5 | +2.6 | 82.8 | 112.3 | **+29.5** | 0.21 | 0.18 | −0.03 |
| Taiwan | 2033 | 2726 | +693 | – | 957 | +957 | 9.9 | 27.5 | +17.6 | 0 | 18.7 | **+18.7** | 0.00 | 0.13 | +0.13 |
| China | 2873 | 4660 | +1787 | 1075 | 1377 | +302 | 124.4 | 161.4 | +37.1 | 50.0 | 65.4 | **+15.4** | 0.29 | 0.46 | +0.17 |
| Germany | 2580 | 3592 | +1012 | 1706 | 1930 | +224 | 15.8 | 21.6 | +5.8 | 20.5 | 30.4 | **+9.9** | 0.05 | 0.06 | +0.01 |
| India | 1214 | 1910 | +696 | – | 1276 | +1276 | 0.8 | 1.1 | +0.3 | 0 | 8.8 | **+8.8** | 0.00 | 0.03 | +0.03 |
| Netherlands | 2042 | 2763 | +721 | 1225 | 1421 | +196 | 17.3 | 19.2 | +1.9 | 20.0 | 28.3 | **+8.3** | 0.04 | 0.05 | +0.01 |
| Japan | 2194 | 2897 | +703 | 1390 | 1522 | +132 | 21.0 | 30.1 | +9.1 | 19.0 | 19.0 | **0.0** | 0.03 | 0.03 | 0.00 |
| Mexico | 1734 | 2118 | +384 | 1026 | 1221 | +195 | 28.1 | 45.4 | +17.3 | 11.2 | 13.9 | **+2.7** | 0.02 | 0.03 | +0.01 |
| Viet Nam | 1146 | 1540 | +394 | 710 | 906 | +196 | 2.4 | 4.1 | +1.7 | 1.5 | 4.4 | **+2.9** | 0.00 | 0.01 | +0.01 |
| France | 1940 | 2504 | +564 | 1160 | 1306 | +146 | 12.1 | 14.6 | +2.5 | 10.4 | 13.0 | **+2.6** | 0.02 | 0.03 | +0.01 |

Source: United Nations Comtrade Database. Table: Authors. Note: All indicators are computed on the directed, weighted network of final digital goods trade. In-degree/out-degree measure the number of distinct import/export links (counts of incoming/outgoing bilateral trade connections). In-strength/out-strength measure the total imported/exported value (sum of trade values across all incoming/outgoing links), in billions of current US dollars. Betweenness (Betw) indicates the extent to which a country acts as a bridge connecting other countries' trade relationships (higher values imply stronger intermediary/broker role). A dash (–) denotes zero or not observed for that indicator in the corresponding year (e.g. no recorded outgoing links). Δ denotes the change from 2012 to 2019.

In terms of leading country blocs, the final goods trade reveals that advanced economies continue to play significant roles. The United States and Germany together exported nearly as much as China in 2019, and the US influence is strong in its hemisphere. Europe collectively is a major producer of final DPT. Japan and South Korea also contribute, though China has eclipsed them individually. Emerging Asia (excluding China) was less dominant in final goods than in parts – for example, ASEAN countries' final goods exports are growing but remain modest. This suggests that while assembly of parts is spreading in Asia, brand-name final production might still be concentrated or not fully captured in this category for those countries.

### 4.3. Parts and components network

Trade in parts and components forms the backbone of global electronics supply chains, reflecting deep international production fragmentation and the dense interlinkages of 'Factory Asia.'

The parts network has the highest reciprocity (41%) and lowest modularity (0.10 by 2019). High reciprocity means many countries both import and export parts, consistent with the idea of multi-stage value chains, where countries specialise in certain stages but also require inputs. Low modularity suggests the community divisions are weakest here; the parts network is truly global with tightly interwoven cross-regional supply chains. While we still detect three communities, they are less geographically segmented. For instance, in the parts trade, Brazil and India were part of the Asia-centric cluster (unlike in final goods), likely because they import many parts from China/Asia for their local industries. The European cluster, in parts, is smaller and less isolated, as European industry must source many components from Asia, too. The Americas cluster likewise is less pronounced – the US, Mexico, and Canada trade parts among themselves, but also heavily with Asia. The resulting picture is a complex network where Asia serves as the central hub, connecting to everyone (hence China's massive betweenness in this network).

From a bloc of countries' perspective, East and Southeast Asian economies form the core of the parts network. Not only China, Japan, Korea, and Taiwan, but also Malaysia, Vietnam, Thailand, the Philippines, and Indonesia collectively account for the majority of flows. North America (USA, Mexico and Canada) is another essential block, but more as a consumer/importer of parts (for assembly plants in Mexico or to supply high-end manufacturing in the US) and as a niche exporter (USA of semiconductors, aerospace electronics; Mexico of auto-electronics, etc.). Europe appears more peripheral in certain areas: it relies on importing components. This indicates Europe's electronics industries are relatively minor or have offshored component production. Meanwhile, China's role as both the largest supplier and buyer means it links all blocks – it buys from East Asia (Taiwan, Korea, Japan), ASEAN, and even from the West (semiconductors from the US/Europe), and in turn sells parts to many countries for further assembly. This places China at the centre of the network as a *broker* between different regional production systems.

As can be observed on Table 4, a final point to note is the rise of Vietnam and Malaysia (and to an extent Thailand and the Philippines) in this period, which has expanded the Asian production bloc. In network

**Table 4.** Node-level characteristics for parts & components (category 3), 2012–2019.

| Country | In-deg 2012 | In-deg 2019 | Δ In | Out-deg 2012 | Out-deg 2019 | Δ Out | In-str 2012 | In-str 2019 | Δ In-str | Out-str 2012 | Out-str 2019 | Δ Out-str | Betw 2012 | Betw 2019 | Δ Betw |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| China | 1770 | 2357 | +587 | 1285 | 1349 | +64 | 209.3 | 295.8 | +86.5 | 260.8 | 387.7 | **+126.8** | 0.36 | 2.16 | +1.80 |
| Hong Kong | 1241 | 1434 | +193 | 836 | 864 | +28 | 4.5 | 13.4 | +8.9 | 136.1 | 216.4 | **+80.3** | 0.10 | 0.17 | +0.08 |
| Taiwan | 1430 | 1626 | +196 | 0 | 875 | +875 | 128.0 | 231.4 | +103.3 | 0 | 67.4 | **+67.4** | 0.00 | 0.36 | +0.36 |
| Malaysia | 1192 | 1385 | +193 | 0 | 800 | +800 | 65.9 | 102.6 | +36.7 | 0 | 37.1 | **+37.1** | 0.00 | 0.04 | +0.04 |
| Viet Nam | 527 | 911 | +384 | 614 | 675 | +61 | 6.8 | 57.0 | +50.2 | 12.9 | 49.1 | **+36.2** | 0.00 | 0.02 | +0.02 |
| Rep. Korea | 1017 | 1315 | +298 | 863 | 967 | +104 | 100.7 | 155.6 | +54.9 | 33.4 | 57.5 | **+24.1** | 0.04 | 0.06 | +0.02 |
| USA | 1294 | 1510 | +216 | 1002 | 1056 | +54 | 48.7 | 63.7 | +15.0 | 58.7 | 75.1 | **+16.4** | 0.07 | 0.08 | +0.01 |
| Philippines | 642 | 842 | +200 | 0 | 753 | +753 | 16.8 | 35.1 | +18.3 | 0 | 21.6 | **+21.6** | 0.00 | 0.00 | +0.00 |
| Singapore | 1130 | 1376 | +246 | 967 | 1022 | +55 | 35.9 | 53.7 | +17.8 | 65.7 | 75.1 | **+9.4** | 0.05 | 0.06 | +0.01 |
| Germany | 1115 | 1305 | +190 | 1008 | 1057 | +49 | 23.6 | 24.9 | +1.3 | 23.6 | 31.2 | **+7.6** | 0.03 | 0.04 | +0.01 |

Source: United Nations Comtrade Database. Table: Authors. Note: The table reports node-level metrics for the parts and components (intermediate) DPT sub-network, modelled as a directed, weighted trade network. In-degree counts the number of incoming trade links (how many distinct import connections a country has), while out-degree counts outgoing trade links (how many export connections it maintains). In-strength/out-strength are the aggregate import/export values (sum of incoming/outgoing link weights), expressed in billions of current US dollars. Betweenness (Betw) measures a country's intermediation within the global supply-chain web: higher values indicate a greater tendency to sit on shortest paths and connect otherwise weakly linked trading partners. Δ reports the change between 2019 and 2012.

terms, these countries significantly increased their degree (number of trade partners and products) and strength from 2012 to 2019, moving them closer to the core of the periphery. Vietnam's leap to the top 10 in both importing and exporting of parts is one of the strongest signals of supply-chain reorganisation – likely driven by multinational firms diversifying production (e.g. shifting some assembly from China to Vietnam). Malaysia's high imports and exports of parts reflect its specialisation in semiconductor fabrication and testing (Penang's electronics cluster). These emerging hubs add resilience and complexity to the network, reducing reliance on any single supplier country.

### 4.4. Digital technology instruments network

Instruments for digital technology include capital equipment, precision instruments, and machinery used in digital product manufacturing (e.g. semiconductor fabrication equipment, specialised tools, as well as scientific and measuring instruments). This segment has a somewhat different profile, as it often overlaps with high-tech capital goods typically produced by advanced economies; however, China is also increasingly active in this area.

The network structure for instruments had the highest modularity in 2012 (0.253), which decreased to 0.202 in 2019, but remained higher than in other categories. This implies that regional clusters are relatively strongest in the instruments trade. Likely, we have one cluster with Europe (Germany, UK, France, Netherlands, etc.) trading instruments among themselves and with some markets; another cluster with the US and Americas (since US, Canada, Mexico exchange instruments, and the US buys from Europe and Japan); and an Asia cluster where Japan, Korea, China, Taiwan trade instruments. Interestingly, in the 2019 cluster assignment, the USA fell into the same community as some emerging economies for instruments (community labels can swap, but our analysis on instruments shows that the USA and Brazil together in one cluster, and China and India in another). By 2019, China might form its own cluster with some Asian partners in instruments – possibly reflecting that China sources a significant amount from Japan/Korea (intra-Asia), while the US sources from both Europe and Asia, making the clustering less clear-cut.

Compared to parts, the instrument network is less dense and more one-directional, with reciprocity at only ~36–38%. Many countries only import instruments (e.g. countries without the capacity to produce advanced machinery). The largest strongly connected component in 2012 comprised 101 countries, growing to 131 in 2019 – implying that by 2019, 131 countries both imported and exported at least something in this category, which is surprising and suggests that smaller countries exported minor amounts of instruments (perhaps re-export or niche products). However, over 100 countries remain one-directional in this regard (pure importers). The clustering is high (0.65 globally in 2019), indicating that triads of instrument trade exist (e.g. if A sells to B and C, it is likely that B and C also trade some instruments, possibly via standard suppliers). The assortativity is negative (−0.38 in 2019), reflecting again a hub-periphery pattern: large instrument exporters (such as Germany, the US, Japan, and China) sell to many smaller, import-only countries.

From a country blocs perspective, as we observe in Table 5, the instruments trade is where advanced economies (US, Germany, Japan, Korea, Netherlands) traditionally held technological advantages, though China has rapidly entered. As of 2019, China is the top exporter; however, it is unclear whether this is primarily due to the lower-tech instruments. The US, EU, and Japan still dominate the very high-tech capital equipment segment (e.g. lithography machines from the Netherlands, high-end semiconductor equipment from the US/Japan). The data suggests that transatlantic trade and transpacific trade in instruments are significant: the US and Germany both appear as each other's major partners (both import and export around $31b, likely exchanging different specialised tools). Asia's internal trade (China-Japan-Korea) is also important as they build their semiconductor industries. Developing countries mostly appear as recipients of instruments (for setting up production lines or telecom infrastructure).

## 5. Discussion

Our multi-layer mapping of digital product technologies reveals a network that is simultaneously more connected and more hierarchical (Kostoska et al. 2020). Between 2012 and 2019, links, reciprocity, and the size of the largest strongly connected component all rose, something that indicates a two-way participation beyond buyer-seller. Yet concentration and hierarchy persist: China's betweenness increased sharply, and

**Table 5.** Node-level characteristics for digital instruments, 2012–2019.

| Country | In-deg 2012 | In-deg 2019 | Δ In | Out-deg 2012 | Out-deg 2019 | Δ Out | In-str 2012 | In-str 2019 | Δ In-str | Out-str 2012 | Out-str 2019 | Δ Out-str | Betw 2012 | Betw 2019 | Δ Betw |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Taiwan | 3076 | 3682 | +606 | 0 | 1837 | +1837 | 19.5 | 13.0 | −6.5 | 0 | 8.6 | **+8.6** | 0.00 | 0.00 | 0.00 |
| USA | 4389 | 5660 | +1271 | 2725 | 2901 | +176 | 33.0 | 33.6 | +0.6 | 26.4 | 31.7 | **+5.3** | 0.24 | 0.30 | +0.06 |
| India | 2576 | 3870 | +1294 | 0 | 2151 | +2151 | 0.7 | 1.1 | +0.4 | 0 | 4.9 | **+4.9** | 0.00 | 0.02 | +0.02 |
| Viet Nam | 683 | 1567 | +884 | 1460 | 1567 | +107 | 0.3 | 2.0 | +1.7 | 0.9 | 5.0 | **+4.1** | 0.00 | 0.00 | 0.00 |
| Malaysia | 2203 | 2883 | +680 | 0 | 1770 | +1770 | 4.8 | 7.8 | +3.0 | 0 | 3.5 | **+3.5** | 0.00 | 0.01 | +0.01 |
| China | 2811 | 3070 | +259 | 1855 | 1959 | +104 | 22.1 | 31.6 | +9.5 | 81.4 | 60.3 | **−21.1** | 0.18 | 0.22 | +0.04 |
| Germany | 3265 | 3915 | +650 | 2142 | 2302 | +160 | 21.0 | 31.5 | +10.5 | 14.3 | 17.5 | **+3.2** | 0.12 | 0.14 | +0.02 |
| Japan | 2672 | 3350 | +678 | 1834 | 1936 | +102 | 16.8 | 25.6 | +8.8 | 8.6 | 10.2 | **+1.6** | 0.10 | 0.12 | +0.02 |
| Rep. Korea | 2510 | 2880 | +370 | 1698 | 1810 | +112 | 11.5 | 13.9 | +2.4 | 10.7 | 9.6 | −1.1 | 0.08 | 0.09 | +0.01 |
| Netherlands | 1905 | 2430 | +525 | 1233 | 1366 | +133 | 7.4 | 9.8 | +2.4 | 6.9 | 8.1 | +1.2 | 0.03 | 0.04 | +0.01 |

Source: United Nations Comtrade Database. Table: Authors.

Note: Metrics are computed for the digital instruments sub-network and reflect a directed, weighted structure of exports and imports. In-degree /out-degree capture the number of distinct import/export connections (counts of incoming/outgoing bilateral links). In-strength/out-strength capture the total value traded (sum of link weights), reported in billions of current US dollars. Betweenness (Betw) summarises a country's role as a network connector (broker) between other trading partners; higher values indicate greater potential to channel trade connectivity through that node. Δ denotes the change from 2012 to 2019; a dash (–) indicates zero or not observed for the respective indicator.

the top exporters still capture the bulk of trade flows, consistent with a single-hub core bridging other regionalised blocs.

There are increasing signs of a core-periphery structure, which has partially changed yet also reinforced itself over time. The instruments layer most clearly exhibits a classic core – periphery, with advanced economies (and increasingly China) that retain strong positions (Shin, Kraemer, and Dedrick 2012). High modularity, lower reciprocity, and many one-way importers point to a small club of advanced producers supplying a wide periphery that cannot reciprocate with similar technology and machinery. Examples of this dynamism are Europe as an equipment maker anchoring customers in Eastern Europe and Africa; the US supplies the Americas; Japan and South Korea supply Asia. China's emergence as a capital-goods supplier appears to carve new countries, likely among Belt-and-Road Initiative (BRI) partners, reshaping community boundaries without overturning core dominance (Zou et al. 2022). Recent analyses show that, between 2022 and 2023, Chinese exports of robots to BRI countries increased by 123%, against 48% for non-BRIs (Andreoni, Frattini, and Prodi 2026).

By contrast, the parts-and-components network displays the most 'globalised' structure – highest reciprocity and the weakest community partitioning – mirroring the deep fragmentation of production in electronics. Factory Asia acts as an integrator that both imports sophisticated inputs and exports sub-systems at scale, pulling in ASEAN latecomers (Vietnam, Malaysia, Philippines) whose rising degrees/strengths signal upgrading into mid-stream niches. This is consistent with classic upgrading pathways for latecomer electronics firms that learn by manufacturing parts, leveraging modular architectures and standard interfaces (Hobday 1995; Pietrobelli and Rabellotti 2011).

Final goods trade sits between these contrasting poles. It remains more regionalised and less reciprocal than parts, reflecting branding, standards and regulation, and logistics/after-sales dynamics that favour geographical proximity. The American continent clusters around the US; Europe maintains its own sphere; Asia is China-centred yet increasingly diversified. Notably, more countries move into the final-goods network over time, suggesting the spread of assembly/re-export capabilities even where overall technological capabilities remain thin. This might be consistent with the long trend of value chain catching up in assembly as a low-value adding segment, where most countries that enter the network locate in early stages (Shin, Kraemer, and Dedrick 2012).

Overall, when we focus on peripheral countries, especially low- and middle-income countries, changes in trade structures should be carefully interpreted and heterogeneity remains significant. Changes in country positions – as the one observed for Vietnam, but also Malaysia and Philippines – clearly reflect a major engagement of these economies with DPTs, however it does not necessarily imply technological upgrading. Trade engagement is often necessary for technological upgrading, but it is certainly not a sufficient condition. Engagement of these economies might be either the result of increased supply capacity due to FDIs or domestic investments or simply increasing intermediate and final demand pull. For these changes in supply and demand to result in technological upgrading much more must happen in terms of technology-intensity of investments, ownership and diffusion of technology, and changes in value chain specialisation and local technological linkages development.

Globally, there are three main blocks. First, countries like China, ASEAN, Taiwan, and India are the clear winners in parts and increasingly competitive in final goods; China is beginning to assert itself in instruments, confirming how digitalisation accelerated China's export-technology complexity and upgrading, while reinforcing its centrality in the global digital economy (Liang and Tan 2024). Second, advanced economies (US, EU, Japan, Korea, Netherlands) remain pivotal in instruments and in high-end components, pointing again at a strong path dependency of how high-tech capabilities shape where value concentrates (Agostino et al. 2025; Nam and Barnett 2011; Shin, Kraemer, and Dedrick 2009). Third, most of Africa and much of Latin America (outside Mexico/Brazil) sit at the periphery across all layers, primarily as net importers of both instruments and finals; a handful of middle-income economies (Mexico, Turkey, Brazil) play niche roles linked to regional trade agreements and specific industrial bases (Gereffi 2019). Together, these findings underline a world where denser ties have not dismissed hierarchy; rather, they have reconfigured it, opening selective upgrading windows while entrenching core control in capital-goods and standards-intensive niches.

## 6. Conclusions

This paper introduces a new classification to study digitalisation based on a structural understanding of the technologies underpinning the digitalisation process, which offers a novel way to analyse global DPT trade networks' structure and evolving dynamics. By focusing on production technologies with digital potential and excluding consumables, we achieve a finer granularity with a classification that includes products at different levels of the digitalisation process. Our paper expands the literature on attempts to capture digitalisation in three main ways: first, the use of HS data makes our classification a tool for analysts and policymakers with the highest geographical coverage; second, by going beyond advanced digital production technologies and including products with digital potential, our classification is also a tool to study the diffusion of DPT in emerging and developing countries that might not be already able to produce the most advanced digital products (such as industrial robots, 3D printers, AI hardware components), yet might be in a 'climbing up' phase producing parts and components of advanced digital technologies. Third, by employing our classification in a network analysis, we provide insights into the evolution of the structure underpinning processes of digital technologies diffusion across countries. DPT rely on an intense import-export relationship, which we capture and use to depict the global landscape in production technologies with digital potential.

Our Digital Production Technology Classification (DPTC) offers the potential for future research in several areas. Future work could narrow the analysis down to specific product categories vital to new technologies, like artificial intelligence, mapping the digital value chain and tracking countries' progress along these chains. Also, the geopolitical relevance of our classification opens research paths into the manufacture of crucial technologies, new forms of technological dependence and the possibility of strategic alliances between countries addressing industrial challenges. Finally, a broader reflection on policy implications for developing countries could also indicate an avenue for future research, for example, considering attempts of industrial policy in developing countries around instrumentations and more sophisticated products, to reduce dependency on imported capital goods, and/or supplier development programmes tied to standards participation, with the overarching aim to move away from non-reciprocal exchanges.

Our study also has limitations, particularly the omission of services due to the unavailability of comparable international data. This is a significant oversight given the crucial role of software and services in digitalisation and new technologies. Furthermore, our time-bound analysis, limited to snapshots with the most recent in 2019, misses the effects of recent disruptions in global supply chains and geopolitical changes. Overcoming these limitations calls for the development of new data and analytical approaches in forthcoming research.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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