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Assessing the Readiness of Textile-Exporting Countries for the EU Digital Product Passport

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Abstract

The European Union's Digital Product Passport (DPP), entering into force under the Ecodesign for Sustainable Products Regulation, will require textile exporters to provide traceable, standardised product data across the value chain. Yet little systematic evidence exists on the readiness of the EU's textile-exporting partners to meet this requirement. This thesis addresses that gap by asking: how ready are textile-exporting countries to adopt the DPP, and how can this readiness be assessed and quantified? Using a three-part methodology, hierarchical cluster analysis, panel-data econometrics, and an exposure-readiness matrix, applied to the EU's largest textile-exporting partners over 2010–2023, the thesis develops a replicable, quantified readiness framework spanning technological (FTR), regulatory (RQ), and supply chain concentration (HHI) dimensions. The cluster analysis identifies a clear three-tiered readiness structure, separating advanced, mid-tier, and emerging/developing economies. The panel regressions show that, historically, EU market share has been shaped primarily by structural differences between countries rather than by within-country improvements in readiness over time. Notably, supply chain concentration (HHI) is the single most robust and statistically significant predictor of EU market share ($\beta = 0.0085$, $p = 0.001$), outperforming both technological and regulatory readiness indicators. The exposure-readiness matrix identifies Bangladesh, Turkiye, and Pakistan as the most structurally vulnerable exporters, combining high EU market share with low composite readiness. These findings inform targeted policy recommendations for phased DPP implementation pathways and extend the literature on EU regulatory diffusion and supply chain divergence.

Keywords: Digital Product Passport, ESPR, circular economy, textile supply chains, readiness assessment, supply chain concentration (HHI), panel data analysis

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1. Introduction

"Digital product passports are the golden thread through textile recycling." - Centre for European Policy Studies (2026)

The fashion and textile industry faces major environmental, social, and economic challenges (Legardeur & Ospital, 2024). Over the past decade, textile production and consumption have increased sharply. This has resulted in an unprecedented diversity of products on the market (United Nations Industrial Development Organization, 2025). **Ultra-fast fashion brands** like *Shein* and *Temu* can launch up to **6,000 new products per day**. With their ultra-agile supply chains, very short production lead times, and advanced data capabilities, they continuously create novelty and stimulate demand rather than responding to existing trends (Chen et al., 2025). This business model has serious consequences. It contributes to environmental degradation through excessive water use, pollution, and the release of microplastics. It also creates economic inefficiencies by encouraging overproduction and devaluing the clothing market. In addition, it increases social injustices. These include poor working conditions and disproportionate impacts on vulnerable communities (Dzhengiz et al., 2023).

The environmental and social unsustainability of the fashion and textile industry has caused major criticism among its stakeholders (Abbate et al., 2023; Anh, 2025). Some consumers have gone as far as publicly boycotting certain fashion brands and products (Anh, 2025). The growing awareness of the industry's negative impacts can also be found in the political sphere (Peleg Mizrachi & Tal, 2022). As the collapse of the **Rana Plaza factory** in Bangladesh in 2013 exposed the limits of voluntary corporate self-regulation in global supply chains (Trebilcock, 2020), it also triggered major legislative responses across Western countries (Clerc, 2021; Krajewski et al., 2021; Rühl, 2025) . At the national level, France was the first EU member state to act, adopting the "*Loi relative au devoir de vigilance"* in 2017. This law requires large companies to identify and mitigate human rights and environmental risks across their entire value chain, including those of their suppliers and subcontractors (Kilimcioğlu, 2025). Germany then followed with the *"Lieferkettensorgfaltspflichtengesetz"* (LkSG) in 2021 (Rühl, 2025).

Building on these national precedents, the European Union adopted the "*Corporate Sustainability Due Diligence Directive*" (CSDDD), which entered into force in July 2024 and extends mandatory human rights and environmental due diligence obligations to large companies operating across EU markets, including non-EU firms (Velluti, 2024). Complementing this, the "*Corporate Sustainability Reporting Directive*" (CSRD) expands transparency obligations across the value chain (Hristov & Searcy, 2024), while the ***"Ecodesign for Sustainable Products Regulation"*** **(ESPR)** introduces product-level sustainability requirements for the textile sector, including a ban on the destruction of unsold goods (Stadler et al., 2025). This Regulation also forms part of the broader Strategy for Sustainable and Circular Textiles, supporting the objectives of the European Green Deal (Stadler et al., 2025).

It is within the framework of the ESPR, that the **Digital Product Passport (DPP)** was established. In practice, a Digital Product Passport (DPP) in the textile sector is a digital file or database attached to each garment that stores key information about its origin, materials, production processes and lifecycle, with the aim of improving transparency, traceability and circularity (Vićentijević & Simeunović, 2024). This enables better tracking and management of textile products across their whole value chain (Carvalho et al., 2025). By having product-related information compiled by manufactures the DPP provides the basis for more circular products (Adisorn et al., 2021). It is precisely this connective function that Urban et al. (2026) from CEPS described as the **"golden thread"** running through textile recycling. By making information on fibre composition and material origin accessible at the point of disposal, the DPP is expected to support automated sorting technologies, enabling textiles to be more accurately separated into streams for reuse, mechanical recycling, or chemical recycling. This is a precondition for reintegrating garments into the circular economy that the ESPR aims to foster (Zhang & Seuring, 2024).

However, realising this "golden thread" in practice faces substantial barriers. Beyond firm-level challenges such as high implementation costs, data standardisation, low data-sharing, and general organizational readiness (Acciai & Pérez-Bou, 2025; Domskienė & Gaidule, 2024; Fares et al., 2025), the success of the DPP also depends on the readiness of textile-exporting countries themselves. In 2022, 11 million tonnes of textile products were imported to the EU, with imports coming mainly from China, Bangladesh, and Turkey (European Environment, 2025). Given this scale of dependence on extra-EU suppliers, the

DPP's effectiveness depends on whether these exporting countries possess the technological, regulatory, and organisational capacity to generate and share the required data.

A 2025 UNIDO assessment of Bangladesh, India, and Egypt found uneven readiness across these countries, with significant gaps in policy awareness and supply chain coordination, particularly among SMEs (United Nations Industrial Development Organization, 2025). Nonetheless, this study's small sample and limited geographical scope constrain how far its findings can be generalised. Empirical studies systematically assessing technological, regulatory, and supply-chain readiness across textile-exporting countries are today still largely absent (Karabulut et al., 2025). Addressing this gap is central to understanding adoption barriers and shaping tailored strategies across different geographical contexts (Carvalho et al., 2025).

Rather than seeking to deliver conclusive empirical data regarding the preparedness of a specific nation, this thesis addresses an existing literature gap by developing a methodology for assessing and monitoring readiness. This leads to the following research question:

How can the multi-dimensional readiness of textile-exporting countries to adopt the EU Digital Product Passport be quantified, and how does this structural capacity influence their historical trade dominance in the European Union?

The remainder of this thesis is structured as follows: Section 2 reviews the literature on the DPP and its challenges. Section 3 presents the theoretical framework and hypotheses development and details the methodology, while Section 4 reports the analyses and results. Section 5 discusses the results with theoretical and policy implications. Section 6 concludes with limitations, and directions for future research.

2. Literature review

2.1 Introduction to the Literature

EU environmental policies have significant impacts on the countries with which it trades (Dao, 2023). With the introduction of the Digital Product Passport (DPP), the EU aims to promote sustainability and circular practices in the textile industry, starting in 2029 (European Commission, 2025a). However, concerns about the barriers and challenges to DPP adoption have been raised (Carvalho et al., 2025) and the readiness of textile-exporting countries for this regulation remains uncertain (United Nations Industrial Development Organization, 2025). This literature review investigates the drivers behind the EU's Digital Product Passport (DPP) and its role in transforming the textile industry. It assesses the obstacles to its 2029 rollout while identifying critical gaps in research regarding the preparedness of global exporting countries.

<u>This review is divided into seven parts:</u>

1. EU environmental regulation and global trade: the Brussels Effect
2. The textile industry, circular economy, and supply chain complexity
3. EU sustainability regulation regarding textiles: from CSDDD to ESPR
4. The role of the Digital Product Passport (DPP)
5. Barriers and challenges to DPP implementation
6. Country-level readiness for DPP adoption
7. Gaps in the literature and positioning of this thesis

2.2 Discussion of the Literature

2.2.1 EU environmental regulation and global trade: the Brussels Effect

The European Union is not only a regulator within its own borders but, due to the size and importance of its internal market, often acts as a *de facto* global standard-setter (Bradford, 2012). The EU's ability to regulate global markets in areas such as competition policy, **environmental protection**, and food safety relies not on coercion but on market forces alone. Few global companies can afford not to trade in the EU, and the price of accessing the single market is adjusting production to EU standards, that are often the most stringent globally. This phenomenon, commonly referred to as the *"**Brussels Effect**,"* explains why regulations adopted unilaterally within the EU can have far-reaching consequences for production practices in third countries (Bradford, 2012; Dao, 2023).

However, recent research suggests that this effect is not automatic. In a peer-reviewed study on EU human rights and environmental due diligence regulation in Brazilian soy supply chains, Bastos Lima and Schilling-Vacaflor (2024) argue that exporters can often avoid broad transformation by segmenting production according to different market requirements. They describe this practice as "**supply chain divergence**." Under this model, producers create compliant supply chains for stricter markets such as the EU, while continuing less regulated practices for other destinations.

The study further argues that the effectiveness of EU sustainability regulation is weakened when the EU represents only a limited share of global demand. In such cases, exporters may find it economically viable to isolate EU-compliant production rather than transform their operations as a whole. The authors therefore conclude that a genuine Brussels Effect depends either on other major consumer markets adopting similar standards, or on the EU extending regulatory obligations beyond goods destined solely for the European market.

This argument has direct implications for the textile sector and for the Digital Product Passport (DPP) specifically. In principle, the DPP applies to textile products placed on the EU market regardless of where they are manufactured (European Parliament and Council of the European Union, 2024). If compliance costs remain manageable, and if exporters cannot easily separate EU and non-EU production lines, textile producers may choose to integrate DPP requirements throughout their operations (Bastos Lima & Schilling-Vacaflor, 2024). In that scenario, the DPP could encourage broad improvements in traceability and transparency across global textile supply chains. This outcome reflects the idea of the DPP as a "golden thread" connecting actors and information across the value chain (Urban et al., 2026).

However, the opposite outcome is also possible. If DPP compliance proves costly, and if exporters can maintain separate production systems for different markets, firms may adopt a form of "supply chain divergence" similar to that identified in the soy sector (Bastos Lima & Schilling-Vacaflor, 2024). Producers could channel only EU-bound products through DPP-compliant supply chains while leaving the rest of their operations unchanged. In that case, the transformative impact of the DPP would remain limited to a relatively small segment of global textile production. The broader circularity ambitions of the Ecodesign for Sustainable Products Regulation (ESPR) would therefore be weakened (Council of the European Union, 2023).

2.2.2 The textile industry, circular economy, and supply chain complexity

Understanding the importance of the ESPR and DPP requires a fundamental look at the **circular economy (CE)** and how it applies to textiles. Circular economy is defined broadly around principles of reducing, reusing, and recycling materials (Kirchherr et al., 2017). The Ellen MacArthur Foundation (2017) defines it more precisely as *"a system where materials never become waste and nature is regenerated. In a circular economy, products and materials are kept in circulation through processes like maintenance, reuse, refurbishment, remanufacture, recycling, and composting."*

Today, the textile, apparel, and fashion (TAF) sector remains overwhelmingly linear, organised around a "take-make-dispose" model where products are routinely disposed after use (Alves et al., 2022; Koszewska, 2018; Thomas et al., 2024). Transitioning this sector toward a circular economy requires substantial changes to both production and consumption models (Koszewska, 2018). A recent systematic review analysing 70 peer-reviewed articles on the protective clothing industry identified 655 distinct barriers to CE adoption, clustering them into eleven thematic groups, with technical and technological barriers, knowledge and awareness gaps, and economic constraints emerging as the most prominent (Bulut & Erol, 2026).

For instance, the **structural complexity of textile supply chains** makes monitoring exceptionally difficult. A single garment typically passes through multiple tiers of production: from raw material extraction and fibre processing to spinning, weaving, dyeing, assembly, and retail. Each step is often located in a different country and governed by different regulatory frameworks (Alves et al., 2024). This geographic fragmentation, combined with the involvement of many actors at each stage, makes it extremely difficult for brands to maintain visibility beyond their immediate suppliers (Siliņa et al., 2024). Abbate et al. (2023) note that as supply chains grow longer and more fragmented nowadays, direct contact between stakeholders diminishes. Monitoring compliance with social and environmental standards becomes therefore progressively harder. Some scholars even argue that the inherent complexity of global value chains has been shown to obscure the origin of products and conceal unethical practices (including forced labour and disregard for environmental consequences) from both retailers and end consumers (Badhwar et al., 2023). This structural invisibility reveals a fundamental gap: without reliable, standardised data flowing across all tiers of the value chain, accountability and circularity remain out of reach (Gardner et al., 2019).

2.2.3 EU sustainability regulation regarding textiles: from CSDDD to ESPR

In response to these challenges, the European Commission adopted in March 2022 the **EU Strategy for Sustainable and Circular Textiles**, situating textiles as a priority value chain within the European Green Deal and the 2020 Circular Economy Action Plan. They explained this choice given the sector's significant environmental footprint relative to other consumption categories, with textile consumption in Europe having the fourth highest environmental impact after food, housing and transport (European Commission, 2022). The Strategy set out an integrated legislative agenda combining ecodesign requirements, restrictions on the destruction of unsold goods, harmonised Extended Producer Responsibility rules, measures against microplastic release, and the introduction of the Digital Product Passport for textiles. Two regulatory instruments are particularly central to this agenda and to the question of supply chain transparency: the **Corporate Sustainability Due Diligence Directive (CSDDD)** and the **Ecodesign for Sustainable Products Regulation (ESPR)**.

The CSDDD (Directive 2024/1760), which entered into force in July 2024, establishes obligations for large companies to identify, prevent, mitigate, and account for adverse human rights and environmental impacts arising not only from their own operations but also from those of their subsidiaries and business partners across the value chain (European Commission, 2024a). For apparel and footwear companies, this translates into due diligence obligations covering working conditions in garment factories, the environmental impacts of material sourcing, and risks associated with subcontracting and logistics networks (Jurić et al., 2023). However, the scope and timeline of the CSDDD have since been substantially revised through the **Omnibus I** simplification package. Adopted at the end of 2025 and entering into force in March 2026, the amending Directive (EU) 2026/470 postpones national transposition to 2028 and application to July 2029, narrowing the directive's direct scope considerably (Malone et al., 2025). In practice, only very large companies now fall within scope. These are companies exceeding 5,000 employees and €1.5 billion in net annual turnover, including non-EU firms with equivalent EU-generated turnover (European Commission, 2024a). Given that the vast majority of textile firms operating in or supplying the EU market are micro, small, or medium-sized enterprises, the directive's direct reach is narrow, although indirect compliance pressures are expected to cascade down supply chains through contractual requirements imposed by large buyers (Feld, 2026).

While the CSDDD looks at a company's actions and behaviours, the ESPR sets the specific rules for the products themselves. Proposed in 2022 and entering into force in July 2024, the ESPR establishes a horizontal framework empowering the Commission to set product-specific ecodesign requirements. These relate to durability, reparability, recyclability, recycled content, and the disclosure of information on unsold and discarded products (European Parliament and Council of the European Union, 2024). Within this framework, textiles have been designated a priority product group, and the Regulation explicitly empowers the Commission to introduce a Digital Product Passport as one of its core information-disclosure mechanisms (European Commission, 2024b).

Together, the CSDDD and the ESPR pursue the same broad goal: making textile value chains more transparent and accountable. However, both instruments also reflect the tension raised in section 2.2.1, between the EU's regulatory ambitions and its actual reach over global supply chains. After Omnibus I, fewer companies are directly required to extend due diligence to their suppliers under the CSDDD. Similarly, the ESPR's ecodesign requirements mainly target products sold on the EU market, not the production processes behind them, wherever they take place. It is against this backdrop, and in response to the data and traceability gaps discussed above, that the Digital Product Passport emerges as a tool meant to support supply chain transparency at a larger scale.

2.2.4 The role of the Digital Product Passport (DPP)

As mentioned above, the Digital Product Passport (DPP) is one of the central instruments introduced under the ESPR, anchored in Article 9 and Annex III of the Regulation (European Parliament and Council of the European Union, 2024). By providing lifecycle information on textile products, the DPP aims to support sustainability and circular practices while contributing to the EU's twin transition (Legardeur & Ospital, 2024). Although the ESPR sets no fixed deadline, it allows the Commission to adopt delegated acts defining detailed requirements for priority product groups, including textiles (European Parliament and Council of the European Union, 2024). The Commission has now identified textiles and apparel as a priority sector, with an indicative adoption timeline around 2029 (European Commission & Joint Research Centre, 2025a).

In the latest Joint Research Centre 3rd milestone report the value chain of textile apparel is defined as global, long, complex, fragmented and opaque, with production of a single garment involving at least fifteen supply chain actors across multiple lifecycle stages. This goes from raw material and fibre manufacturing through to retailing (European Commission & Joint Research Centre, 2025b). The DPP therefore aims to solve the major data issues mentioned before. Over 80% of environmental damage happens during raw material production and manufacturing, but this is where data is hardest to find. The DPP isn't just thus for consumers. It creates a standard way to track data across the entire supply chain, including material composition, harmful substances, recycled content and environmental footprints (European Commission & Joint Research Centre, 2025b).

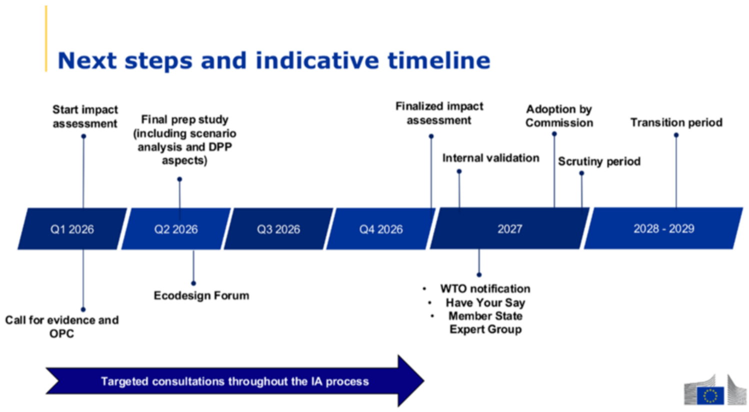
A primary structural limitation of the Digital Product Passport (DPP) is its scope. Under the upcoming textile delegated act, the DPP requirement applies only to final garments placed on the EU market, exempting intermediate products like fabrics, yarns, and fibres (González-Torres & Arcipowska, 2026). This creates a critical traceability and connectivity challenge. While the legal obligation to maintain a DPP falls entirely on the downstream operator selling the final product, the essential data regarding raw material sourcing, material composition, and recycled content originates upstream, long before the legal mandate takes effect (González-Torres & Arcipowska, 2026). Consequently, downstream brands remain heavily dependent on data supplied by upstream actors over whom they exercise limited oversight.

This operational challenge is further intensified by a profound asymmetry in information availability across the textile value chain (González-Torres & Arcipowska, 2026). Although downstream retailers maintain clear visibility over their Tier 1 assembly suppliers through established Enterprise Resource Planning (ERP) systems, visibility drops sharply further upstream. Data concerning Tier 2 fabric mills, Tier 3 yarn manufacturers, and raw material origins remains highly opaque. Upstream actors frequently classify technical specifications as confidential business information and manage these details through unstructured, document-based formats rather than standardized, machine-readable systems (González-Torres & Arcipowska, 2026).

Following the May 2026 Joint Research Centre recommendations, the Digital Product Passport (DPP) would introduce two primary innovations. First, it establishes a harmonized structure for product data. Second, it implements role-based access controls. This ensures that distinct stakeholders, including consumers, customs authorities, and recyclers only access information relevant to their specific functions (González-Torres & Arcipowska, 2026). Interestingly, the ESPR does not mandate comprehensive data sharing across the entire supply chain. It only requires compliance with a strict legal minimum. However, the DPP provides a standardized technical framework. Supply chain actors can voluntarily leverage this foundation to share additional information beyond what the law requires (González-Torres & Arcipowska, 2026).

As illustrated in *Figure 1*, the Commission's indicative timeline foresees the finalization of the impact assessment by late 2026, adoption of the delegated act by the Commission in 2027, followed by a scrutiny period, with a transition period running through 2028–2029 (European Commission & Joint Research Centre, 2025a).

Figure 1: Indicative timeline of the European Commission for the DPP



Source: European Commission and Joint Research Centre (2025a)

2.2.5 Barriers and challenges to DPP implementation

Literature on the Digital Product Passport (DPP) in textiles has evolved from conceptual discussions (2020–2021) to increasingly empirical research as the ESPR gained clarity. Early studies focused on defining the DPP and its potential benefits for sustainability and circular economy practices (Adisorn et al., 2021). Following King et al. (2023), a DPP offers data on sustainability, circularity, hazardous substances, and valuable materials and is shared in an ecosystem among stakeholders across the value chain. Scientific publications on DPPs have increased sharply between 2021 and 2025, reflecting growing academic interest as EU policy matured (Karabulut et al., 2025).

Recent studies explore implementation challenges and propose frameworks. For instance, the technological barriers are a major challenge. Indeed, several authors point to the lack of harmonized data standards and interoperability as a structural barrier: Jansen et al. (2023) note that the absence of agreed-upon data formats, ontologies, and exchange protocols across actors and sectors undermines the cross-value-chain sharing that the DPP concept presupposes, a finding echoed for textiles by the broader fiber-traceability literature (Luoma et al., 2022).

Moreover, a recurring theme in this stream of work is the disproportionate burden placed on small and medium-sized enterprises (SMEs), which dominate the European textile and clothing ecosystem. Carvalho et al. (2025), in a systematic review of DPP implementation in textiles, argue that SMEs may struggle to secure the financial and technological resources needed to adapt, which risks making compliance more accessible to larger, vertically integrated companies and could reinforce existing market concentration.

A further set of challenges relates to the regulatory timeline itself. Several scholars note that because the textile-specific delegated acts under the ESPR are not expected until 2027, companies face a "moving target" problem: investments made now in data infrastructure may not align with finalized technical specifications, creating hesitancy and underinvestment (Acciai & Pérez-Bou, 2025). With the publication of the ESPR Working Plan 2025–2030 and successive milestones of the JRC preparatory study on textiles, this uncertainty is however gradually becoming clearer, as priority requirements are now better defined.

Colasante et al. (2025) showed through a survey that consumer awareness of DPPs remains low, although there is some willingness to pay a premium for these products. More broadly, Zhang and Seuring (2024) identify consumer trust, organizational readiness, and data governance as unresolved challenges for DPP-enabled supply chain management across all contexts. Moreover, Papile and Del Curto (2025) highlighted that data sharing remains uncommon in practice for commercial reasons.

2.2.6 Country-level readiness for DPP adoption

Global supply chains make the readiness of textile-exporting countries particularly relevant. In the Global South, key barriers include high costs and complexity, weak regulatory environments, resistance to organizational change, limited data sharing, and social sustainability issues such as poor labor conditions (Fares et al., 2025). UNIDO’s 2025 white paper assessed supply chain, organizational, and technological readiness in Bangladesh, India, and Egypt. While companies showed willingness to adopt the DPP, readiness was uneven, with major gaps in policy awareness and supply chain coordination, especially among smaller firms. However, the study's small sample (~100 mostly SMEs in three countries) and limited scope constrain broader generalization (United Nations Industrial Development Organization, 2025). Other grey literature sources including a KPMG multi-country survey of European companies (KPMG International, 2026) point to similar patterns of uneven awareness and readiness, though its methodological limitations also constrain generalization. While the EPRS textile DPP study from 2024 explicitly raises the question of how compliance burdens and sustainability verification should extend to non-EU manufacturers, its empirical base consisted of a survey of 81 stakeholders, predominantly from EU countries. This does not yet provide a systematic, quantified assessment of how compliance costs and data-collection burdens are distributed across non-EU supply chain tiers, leaving this as an acknowledged open question rather than an analyzed one (Legardeur & Ospital, 2024).

The barriers identified above, technological immaturity, weak regulatory enforcement (Carvalho et al., 2025; Ducuing & Reich, 2023; Piétron et al., 2023) and structurally fragmented or opaque supply chains (Abbate et al., 2023; Alves et al., 2022; Anh, 2025), are not only obstacles to DPP implementation in the abstract or just for a firm. They map show the conditions under which a country can realistically generate, verify, and share the data the DPP requires. A country lacking digital infrastructure cannot capture and transmit product-level data. Furthermore, a country with weak regulatory enforcement cannot guarantee the data's accuracy or protect it once shared. Finally, a country with highly fragmented, multi-tiered supply chains struggles to trace a single garment back through its full production history.

2.2.7 Gaps in the literature regarding the readiness of textile-exporting countries to the DPP

In conclusion, most current research remains highly qualitative, relying on bibliometric reviews, interviews, or surveys, and often applies basic frameworks such as SWOT or Porter's Cluster Theory, which are not designed to quantify readiness (Colasante et al., 2025; Fares et al., 2025). Empirical studies assessing technological, regulatory, and supply-chain readiness across textile-exporting countries are largely absent. A bibliometric analysis of DPP publications confirms that conceptual and framework-oriented outputs dominate the field, while empirically validated implementation studies remain rare (Karabulut et al., 2025).

Addressing this gap is central to understanding adoption barriers and informing tailored strategies in different geographical contexts (Carvalho et al., 2025).

This tension between EU regulatory ambition and the practical capacity of exporting countries forms the central premise of this thesis. Whether the DPP becomes an effective "golden thread" across global textile value chains, or instead produces a fragmented landscape of selective compliance, depends largely on the readiness of exporting countries. This includes their technological infrastructure, regulatory capacity, institutional coordination, and organisational ability to integrate DPP requirements into production systems as a whole rather than as a market-specific add-on (Bastos Lima & Schilling-Vacaflor, 2024). Examining this readiness gap is the central objective of this thesis.

3. Methodology

3.1 Research question and hypotheses

The literature review highlighted a persistent research gap between the EU's regulatory ambition for the Digital Product Passport and the empirically unverified capacity of exporting countries to comply with it. This study formulates one primary research question, three sub-questions, and three hypotheses to empirically investigate textile-exporting countries' readiness for DPP adoption and its structural implications for EU trade.

Primary research question:

How can the multi-dimensional readiness of textile-exporting countries to adopt the EU Digital Product Passport be quantified, and how does this structural capacity influence their historical trade dominance in the European Union?

This question responds directly to the gap identified in section 2.2.7: existing assessments of country-level readiness, such as the United Nations Industrial Development Organization (2025) white paper on Bangladesh, India, and Egypt, remain small-sample, qualitative, and geographically narrow, leaving the field without a systematic, quantified, and comparative measure of readiness (Karabulut et al., 2025). By developing such a measure and linking it to historical trade performance, this thesis moves the literature from descriptive case studies toward an empirical framework.

Sub-questions:

1. How do high-volume textile exporters to the EU group into distinct readiness profiles when evaluated against digital, regulatory, and supply chain concentration dimensions?

2. To what extent have historical variations in digital infrastructure, regulatory stringency, and supply chain concentration structurally driven an exporter's market share retention in the EU from 2005 to 2024?

3. Which exporting cohorts display the highest risk of structural market exclusion based on the friction between their current EU market share and their lagging macro-readiness scores?

The first hypothesis holds that lower-income exporters display systematically weaker digital, regulatory, and supply chain readiness than their higher-income counterparts, even when the latter hold a smaller share of the EU market. The underlying mechanism is one of accumulated structural lag: decades of cost-driven export growth in lower-income countries have not been accompanied by parallel investment in traceability infrastructure or regulatory alignment with EU standards. Countries such as Bangladesh and Cambodia, for instance, have built substantial EU market share on labour-cost advantages rather than on digital or regulatory capacity (United Nations Industrial Development Organization, 2025). This hypothesis is grounded in the readiness literature reviewed in section 2.2.6, which documents uneven technological and regulatory preparedness among major Global South exporters (Fares et al., 2025).

The second hypothesis asserts that improvements in digital infrastructure and regulatory systems have been a historical driver of EU market share gains, independent of cost competitiveness alone. This hypothesis posits that exporters who invested in digital traceability tools and regulatory convergence with EU standards over the past two decades, secured an advantage in retaining and expanding their position in the EU market. For example, the Brussels Effect literature suggests that exporters able to align early with EU regulatory expectations face lower compliance frictions and are better positioned to deepen trade relationships (Bradford, 2012; Dao, 2023).

The third hypothesis proposes that the DPP will act as a structural barrier to market entry that disproportionately threatens dominant but low-readiness exporting hubs. This hypothesis emphasises that the DPP's documentation, traceability, and data-sharing requirements (European Parliament and Council of the European Union, 2024), will impose adjustment costs that high-volume, low-readiness exporters are least equipped to absorb (Carvalho et al., 2025).

By testing these hypotheses, this study aims to provide the first quantified, cross-country evidence on the relationship between DPP readiness and EU trade dominance in the textile sector, contributing to the academic literature on regulatory readiness and informing policymakers and exporting countries on the risks of structural market exclusion. These hypotheses will be tested using a combination of cluster analysis, econometric modelling, and historical trade data, as detailed in the subsequent research design.

Table 1: Hypotheses overview

H1	Lower-income countries display systematically weaker digital and regulatory and supply chain readiness than higher-income, lower share competitors.
H2	Over the last twenty years, countries that improved their digital infrastructure and regulatory systems achieved a statistically significant increase in their share of the EU textile market.
H3	Exporters combining high EU market share with low composite digital, regulatory and supply-chain readiness constitute a structurally vulnerable cohort, exposed to disproportionate risk under a future DPP compliance regime.

Source: Compiled by the author for the purpose of this thesis.

3.2 Research design and theoretical framework

As the aim of this thesis is to quantify the readiness of textile-exporting countries, a quantitative analysis based on a positivist research paradigm was conducted. Because readiness was examined at the country level rather than at the firm level, the analysis focuses on three core dimensions: technical, regulatory, and supply-chain readiness. These dimensions were chosen based on the literature review and three established frameworks from peer-reviewed literature. First of all, regulatory readiness is needed for the DPP as the passport relies on a government's structural capacity to enforce transparent data standards, protect intellectual property, and prevent market distortions across complex supply chains (Ducuing & Reich, 2023; Piétron et al., 2023). For this, the Institutional Theory explains how regulatory, normative, and cognitive pressures influence organisational responses to regulation and can help explain cross-country differences in regulatory readiness and compliance with the Digital Product Passport (DiMaggio & Powell, 1983; Scott, 2014). Next, a nation's ability to adopt the DPP depends heavily on its digital network infrastructure and targeted R&D funding for data systems. The Dynamic Capabilities Theory addresses firms' and countries' ability to sense, seize, and reconfigure technological and organisational resources in response to external shocks, providing the basis for assessing digital and supply chain readiness (Teece, 2007). Finally, highly diversified and decentralized supply chains make comprehensive track-and-trace data collection exceptionally difficult to execute (Langley et al., 2023). For this, the Global Value Chain (GVC) Governance Theory explains how power asymmetries and coordination structures across buyers and suppliers determine who absorbs the costs of new compliance requirements (Gereffi et al., 2005). These frameworks collectively address regulatory capacity (Institutional Theory), technological and organisational adaptability (Dynamic Capabilities Theory), and supply chain power and concentration (GVC Governance Theory).

3.3 Research methodology

3.3.1 Data sources

The timeframe covers 2005–2023 to track the emergence of ultra-fast fashion; however, because a key index was only introduced in 2010, the econometric analysis is restricted to the 2010–2023 window. 2023 is used as the end date, in line with the UN Comtrade Data Availability checker, as it is the most recent year with complete data coverage (United Nations Statistics Division). The analysis focuses exclusively on fashion-related textile products. Upstream textile production is proxied by HS 50–55 and 58, capturing fiber and fabric stages, while downstream fashion manufacturing is captured by HS 60–62. Household textile products (HS 63) are excluded due to their limited relevance to apparel supply chains. The same goes for codes 56 and 57 that are related to carpets and industrial use. *Table 2* beneath represents the different codes. Databases used include UN Comtrade, World Bank Database, and UNCTAD.

Table 2: HS codes

HS Code	Description	Supply chain stage
HS 50	Silk	Upstream (fibre/fabric)
HS 51	Wool, animal hair	Upstream (fibre/fabric)
HS 52	Cotton	Upstream (fibre/fabric)
HS 53	Other vegetable textile fibres	Upstream (fibre/fabric)
HS 54	Man-made filaments	Upstream (fibre/fabric)
HS 55	Man-made staple fibres	Upstream (fibre/fabric)
HS 58	Special woven/tufted fabrics, lace, trimmings	Upstream (fibre/fabric)
HS 60	Knitted or crocheted fabrics	Downstream (fashion manufacturing)
HS 61	Apparel, knitted or crocheted	Downstream (fashion manufacturing)
HS 62	Apparel, not knitted or crocheted	Downstream (fashion manufacturing)

Source: Compiled by the author for the purpose of this thesis. Data: UNComtrade

3.3.2 Supply-chain readiness & the Herfindahl–Hirschman Index (HHI)

First, publicly available trade data based on Harmonized System (HS) codes was used to examine the structure of global textile supply chains. This allows to assess supply-chain fragmentation, which can be a major barrier to DPP adoption. To measure supply-chain diversification and country-level trade concentration, the Herfindahl–Hirschman Index (HHI) was manually calculated for each country. This index is widely used in trade diversification literature (Cadot et al., 2011). The HHI in this context measures the concentration of a country's import origins. For this, only codes 50-55 and 58 were used, as the aim is to assess upstream diversification which will be a major challenge to DPP implementation. Proxies were used for countries that did not report their imports (see section 4.1.2). The database was combined using Power Queries (Excel).

The HHI is calculated using the following formula:

$$HHI = \sum_{i=1}^{N} (s_i)^2$$

Where:

- s_i is the market share of trading partner i expressed as a fraction (or percentage) of the country's total trade.
- N is the total number of trading partners.

The index ranges from $1/N$ to 1.0. A higher HHI value indicates a highly concentrated trade profile (dependency on a few markets). A lower HHI implies a highly diversified trade network, indicating better supply-chain resilience but also more difficulties to implement the DPP.

3.3.3 Frontier Technologies Readiness Index (technological readiness)

Sourced from the United Nations Conference on Trade and Development (UNCTAD), this index evaluates a country's capacity to use, adopt, and adapt to frontier technologies (e.g., AI, blockchain, IoT) essential for hosting and managing digital product passports. The index is a composite score based on five core pillars: *1) ICT deployment, 2) skills, 3) research and development (R&D) activity, 4) industry activity, and 5) access to finance.*
The index is normalized to score between 0 and 1:

$$Index\ Score = \frac{\sum_{j=1}^{P} w_j I_j}{\sum_{j=1}^{P} w_j}$$

Where:

- I_j represents the normalized score of pillar .

- w_j represents the weight assigned to that pillar.
- P is the total number of pillars ($P = 5$).

3.3.4 World Bank Regulatory Quality Indicator (regulatory readiness)

To capture the macro-level regulatory climates governing textile exporters, this study utilizes the World Bank's Regulatory Quality indicator, one of the six dimensions of the Worldwide Governance Indicators (WGI) project. Sourced from the World Bank, Regulatory Quality captures perceptions of a government's ability to formulate and implement sound policies and regulations that permit and promote private sector development. While the indicator evaluates general regulatory governance rather than textile- or DPP-specific mandates, it serves as a robust proxy for a nation's regulatory maturity, enforcement infrastructure, and systemic capacity to absorb complex compliance requirements like the DPP.

The Regulatory Quality score is constructed by aggregating perception-based data from a large number of underlying sources using an unobserved components model (UCM). This model treats each individual data source as an imperfect signal of the latent, unobserved concept of regulatory quality, and aggregates them into a single composite score:

$$RQ_{c,t} = \frac{\sum_{s=1}^{S} w_s * X_{s,c,t}}{\sum_{s=1}^{S} w_s}$$

Where:

- $RQ_{c,t}$ represents the aggregate Regulatory Quality score for country c in year t, rescaled to a standard normal distribution (approximately −2.5 to 2.5, where higher values indicate stronger regulatory quality).
- $X_{s,c,t}$ represents the rescaled score from individual data source s for country c in year t.
- w_s represents the weight assigned to data source s, derived from the UCM based on the source's reliability (i.e., how closely it correlates with the other sources).
- S is the total number of underlying data sources available for that country-year observation.

3.3.5 Cluster analysis

To objectively categorize the sample countries into distinct readiness profiles without introducing arbitrary human weights, an agglomerative hierarchical cluster analysis was conducted. Clustering was performed using Ward's minimum-variance linkage method, applied to z-score normalized values of the three readiness dimensions to prevent scale bias, with dissimilarity measured via squared Euclidean distance (L2 dissimilarity measure), the standard metric paired with Ward's method. Focusing on the top 20 textile-exporting countries to the EU narrowed the scope of the study while maintaining a sample size robust enough for cluster analysis with three variables (Everitt, 2011).

3.3.6 Econometric model

While the cluster analysis establishes an objective, static taxonomy of contemporary exporter profiles based on normalized Z-scores, it cannot isolate time-varying dynamics, track historical trajectory shifts, or isolate the individual statistical weights of each readiness dimension. To quantify how technical maturity, regulatory environments, and supply-chain configurations influence trade performance, this study applies a longitudinal panel regression spanning the years 2010 to 2024 across 83 countries. To filter the dataset, countries with an EU market share of less than 0.01% were excluded from the analysis.

The empirical relationship is formalized as a multi-variable linear panel model:

$$MarketShare_{it} = \beta_0 + \beta_1 UNCTAD_{it} + \beta_2 EPI_{it} + \beta_3 HHI_{inv,it} + \gamma_i + \delta_t + \varepsilon_{it}$$

Where:

- $MarketShare_{it}$ is the dependent variable, representing the continuous percentage share of total EU clothing textile imports captured by exporting country in year .
- $UNCTAD_{it}$ represents the time-varying technical readiness score.
- EPI_{it} represents the time-varying regulatory and environmental enforcement proxy.
- $HHI_{inv,it}$ represents the inverted trade concentration index (1 - HHI), where higher values signify a highly diversified, resilient trade architecture.
- γ_i represents Country Fixed Effects, which capture and hold constant all unobserved, time-invariant country characteristics (e.g., geographic distance to the European Union, cultural ties, language, and historical baseline institutions).

- δ_t represents Time Fixed Effects, which control for annual global macro-shocks that impact all textile exporters simultaneously (e.g., the 2005 expiration of the Multi-Fiber Arrangement, the 2008 financial crisis, and the 2020 pandemic supply-chain shocks).
- ε_{it} is the idiosyncratic error term, adjusted using robust standard errors clustered at the country level to control for inherent heteroskedasticity and serial correlation across trade panels.

<u>*Rationale:*</u>

Analyzing upcoming trade legislation like the EU's Digital Product Passport introduces a core methodological challenge. Direct post-enforcement empirical data does not yet exist. Modeling this transition through a historical panel from 2010 to 2023 overcomes this limitation. It serves as a predictive stress test of structural supply chain path dependencies rather than a purely retrospective exercise. This approach treats historical trajectories in digital infrastructure as indicators of long term compliance elasticity. If the market historically penalized low tech or structurally weak environments, it validates the premise that upcoming mandates will turn these vulnerabilities into absolute barriers to entry. Furthermore, a longitudinal timeline up to 2023 captures ongoing anticipatory adaptation. This reflects the real time de risking and capital reallocation by multinational brands away from non compliant cohorts years ahead of formal enforcement. By cross validating these historical regression coefficients with contemporary cluster groupings, this framework successfully bridges past behavior and future readiness. It pinpoints whether an exporter's current trade dominance is sustainably insulated or structurally vulnerable to the upcoming digital passport rollout.

Because EU market share is a proportion bounded between 0 and 1 and heavily concentrated near zero, the linear fixed effects model risks biased estimates and predictions outside the valid range (Papke & Wooldridge, 2008). To address this, two additional specifications were estimated. First, a fractional logit model via Generalized Estimating Equations (GEE) was applied, modelling the population-averaged relationship through a logit link that keeps fitted values within [0,1], while accounting for repeated country-year observations. Second, a correlated random effects (Mundlak) model was estimated, augmenting the regression with each variable's country-specific time-average. This decomposes the within-country effect (change in a country's own readiness over time) from the between-country effect (its average readiness relative to other exporters), clarifying cases where the fixed effects and GEE models produced diverging coefficient signs. Together, the three tests form a triangulated robustness strategy: fixed effects isolate within-country variation, fractional logit respects the bounded dependent variable, and Mundlak separates within- from between-country sources of the relationship.

3.4 Methodological limitations

A primary challenge of this study is that the regulatory landscape remains a moving target, as the European Commission is currently conducting its impact assessment and has yet to release final DPP technical specifications (European Commission & Joint Research Centre, 2025a). Consequently, sector-specific data for textiles does not yet exist. Data scarcity across developing countries further precluded the use of a Principal Component Analysis (PCA) on relevant sub-indicators. Moreover, the initial research design of conducting semi-structured interviews proved unfeasible due to a lack of available policymakers and industry professionals with sufficient expertise at this early stage of implementation. The analysis relies heavily on macro-level, aggregated international trade data. Consequently, it cannot directly capture firm-level production nuances, sub-national regional industrial clusters, or the highly fragmented, informal subcontracting layers common in global apparel supply chains. While the UNCTAD Frontier Technologies Readiness Index and the World Bank Regulatory Quality Index offer powerful, peer-reviewed insights into national capacities, they reflect broad cross-sectoral capabilities rather than textile-specific infrastructures. The immense developmental gaps between the sampled countries (United States and Japan alongside developing nations like Bangladesh and Cambodia) introduce high multidimensionality.

4. Results

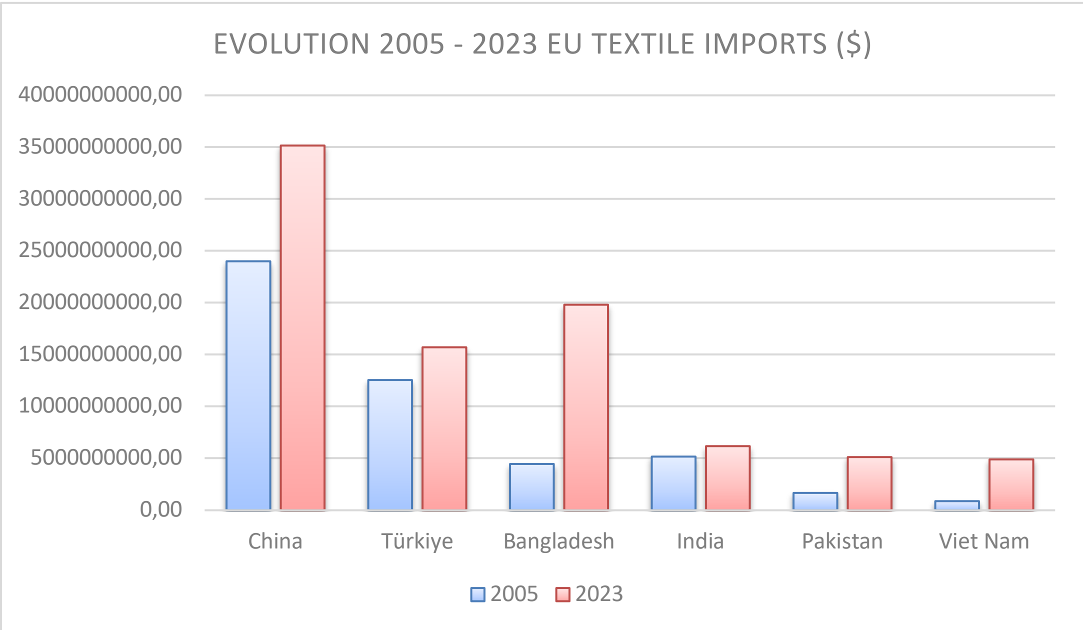
This section presents the empirical findings of the study, structured around the three hypotheses introduced in section 3.1. A cluster analysis first identifies distinct readiness profiles among the EU's major textile exporters (H1), followed by a panel-data econometric analysis of how these readiness dimensions relate to EU market share over time (H2). Finally, an exposure-readiness matrix assesses which exporters face the greatest structural risk under the upcoming Digital Product Passport (H3).

4.1 Descriptive statistics

4.1.1 EU textile imports

To contextualize where Digital Product Passport (DPP) compliance pressures will be most acutely felt, this section examines the evolution of textile imports into the European Union from 2005 to 2023.

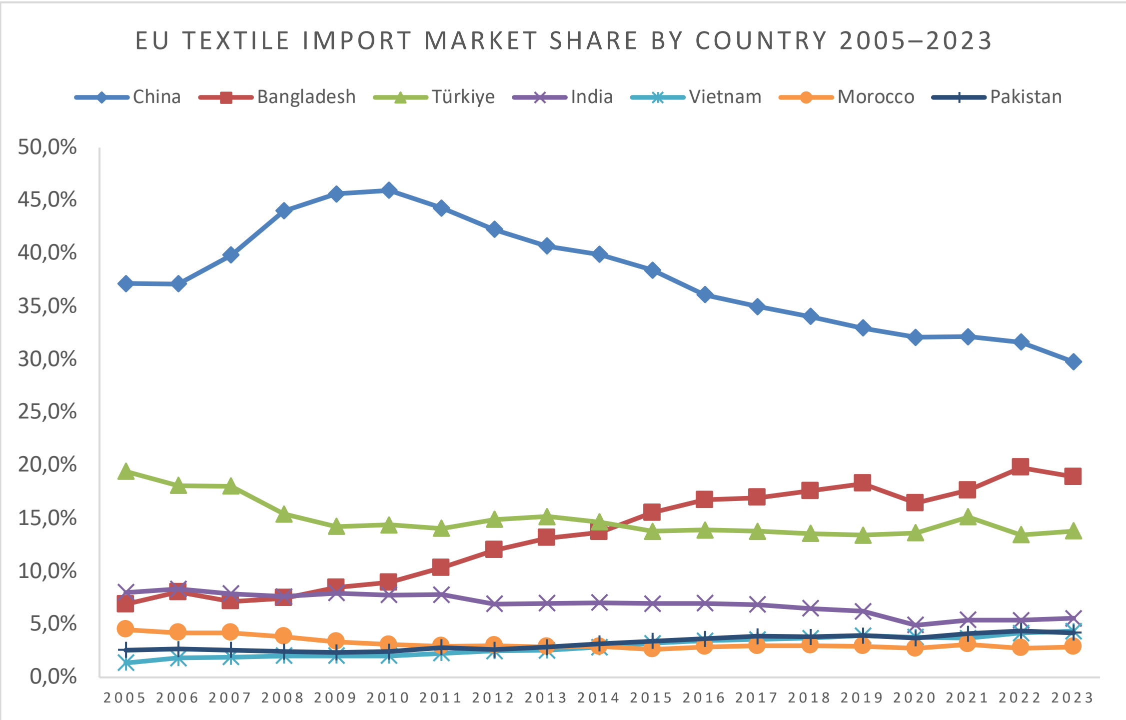
Figure 2: EU imports of clothing textile evolution from 2005 - 2023



Source: Computed by the author for the purpose of this thesis using Excel. Data: UN Comtrade

In absolute value terms, Chinese textile imports expanded intensely, climbing from approximately $24 billion in 2005 to around $35 billion by 2023. Bangladesh emerged as the fastest-growing competitor, experiencing a steep rise that positioned it as the second-largest exporter on the chart by 2023 with $20 billion. This expansion contrasts sharply with long-term partners like Türkiye and India, both of which maintained remarkably flat, stabilized import volumes over the same nineteen-year period. As a robustness check, these values were compared with those reported in EURATEX's 2024 textiles report, although these values were measured in euros (EURATEX, 2024). Even though China is still the biggest exporter to the EU in terms of textiles, China's overall EU market share contracted from its 2010 peak of 46.1% and it stabilized at 30% in 2023 as can be seen in *Figure 3*.

Figure 3: EU imports of clothing textile - market share trends 2005–2025



<u>*Source:*</u> Computed by the author for the purpose of this thesis using Excel. <u>Data:</u> UN Comtrade

Bangladesh represents the most aggressive supply chain expansion in the dataset. Its EU market share nearly tripled, climbing continuously from 6.9% in 2005 to 18.9% by 2023. This massive structural shift positions Bangladesh as a critical point for trace-and-track compliance infrastructure. Vietnam and Pakistan showed notable growth trajectories, scaling their respective market shares to 4.4% and 4.2% by 2023. Furthermore, despite geographic proximity to the Eurozone, traditional nearshoring hubs experienced relative market share decline. Türkiye witnessed a steady contraction, dropping from 19.4% in 2005 to 13.8% in 2023. Similarly, Morocco maintained a marginal, stagnant market share fluctuating around 2.9% by 2023.

4.1.2 Indices and cluster analysis

To evaluate macroeconomic capability for implementing Digital Product Passports, three indicators were gathered and normalized:

1. **Herfindahl-Hirschman Index (HHI):** Formulated from raw trade data to evaluate trade concentration. Peer-reviewed studies on the DPP explicitly establish that highly diversified and fragmented global supply chains (low HHI) create massive hurdles for trace-and-track data collection (Langley et al., 2023).

2. **Frontier Technologies Readiness Index (FTR):** A proxy for baseline technological maturity (ICT deployment, digital skills, local R&D). Existing literature indicates that a country's capacity to adapt the Digital Product Passport (DPP) is heavily reliant upon its technological maturity, specifically regarding digital infrastructure and targeted R&D investment in data systems (Carvalho et al., 2025).

3. **Regulatory Quality Index (RQ):** A proxy for national regulatory enforcement and state-level sustainability frameworks. The index measures the government's ability to create and enforce sound, transparent rules (World Bank, 2024). A high regulatory quality score is crucial for DPP implementation because the passport relies on a government's structural capacity to enforce transparent data standards, protect intellectual property, and prevent market distortions across complex supply chains (Carvalho et al., 2025; Ducuing & Reich, 2023; Piétron et al., 2023).

An overview of the indices is presented on the subsequent page in *Tables 3, 4, and 5* (covering HHI, FTR, and RQ, respectively). While HHI calculations began in 2005, the data displayed spans 2010 to 2023. This tracking period begins in 2010 to match the launch of the FTR indicator and to capture the era when modern technological capabilities became normalized across global value chains. Moreover, for the HHI import data was used for raw and intermediate materials (HS code 50-55 and 58). Where such data were unavailable, exports reported by all other countries to the importing country were used as a proxy. This approach requires comprehensive reporting from all exporting countries, which is not always satisfied. The resulting estimates are likely to be slightly upward biased, implying a higher degree of trade concentration than is present. These proxies are highlighted in grey in the *Table 3.*

Table 3: Country-level annual HHI for raw and intermediate textile imports, 2010–2023

COUNTRY	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Albania	0,323	0,329	0,324	0,316	0,262	0,290	0,350	0,328	0,321	0,331	0,275	0,318	0,340	0,316
Argentina	0,156	0,161	0,159	0,153	0,151	0,146	0,173	0,210	0,182	0,193	0,202	0,204	0,262	0,260
Armenia	0,161	0,162	0,117	0,166	0,174	0,183	0,151	0,192	0,161	0,136	0,141	0,151	0,128	0,117
Australia	0,084	0,099	0,104	0,105	0,115	0,123	0,128	0,135	0,131	0,124	0,141	0,136	0,153	0,158
Bahrain	0,158	0,163	0,150	0,166	0,180	0,196	0,133	0,126	0,120	0,108	0,134	0,143	0,119	0,184
Bangladesh	0,141	0,156	0,151	0,162	0,278	0,176	0,179	0,168	0,137	0,266	0,247	0,263	0,257	0,260
Belarus	0,127	0,114	0,159	0,172	0,186	0,177	0,152	0,161	0,147	0,157	0,154	0,152	0,190	0,195
Bolivia (Plurinational State of)	0,240	0,275	0,247	0,233	0,244	0,261	0,290	0,328	0,310	0,261	0,241	0,252	0,274	0,295
Bosnia Herzegovina	0,147	0,145	0,129	0,135	0,133	0,127	0,138	0,133	0,154	0,156	0,143	0,151	0,145	0,144
Brazil	0,147	0,162	0,187	0,212	0,218	0,242	0,246	0,254	0,260	0,316	0,358	0,333	0,437	0,467
Burkina Faso	0,230	0,207	0,196	0,203	0,301	0,268	0,304	0,267	0,250	0,266	0,330	0,385	0,413	0,552
Cabo Verde	0,649	0,727	0,686	0,575	0,528	0,619	0,422	0,584	0,496	0,655	0,707	0,570	0,667	0,770
Cambodia	0,283	0,354	0,408	0,421	0,429	0,508	0,546	0,575	0,570	0,556	0,559	0,543	0,559	0,614
Cameroon	0,344	0,353	0,413	0,354	0,448	0,464	0,340	0,465	0,503	0,509	0,445	0,328	0,283	0,288
Canada	0,223	0,216	0,221	0,218	0,219	0,207	0,210	0,209	0,190	0,178	0,179	0,163	0,159	0,170
Chile	0,256	0,283	0,293	0,311	0,340	0,330	0,369	0,370	0,329	0,331	0,302	0,340	0,405	0,456
China	0,076	0,080	0,082	0,080	0,072	0,067	0,068	0,070	0,070	0,067	0,069	0,072	0,084	0,072
China, Hong Kong SAR	0,369	0,371	0,381	0,399	0,398	0,410	0,419	0,403	0,432	0,435	0,439	0,433	0,343	0,370
China, Macao SAR	0,452	0,362	0,435	0,326	0,376	0,423	0,542	0,465	0,242	0,220	0,555	0,416	0,260	0,704
Colombia	0,125	0,138	0,139	0,154	0,172	0,183	0,197	0,198	0,220	0,245	0,235	0,240	0,250	0,298
Costa Rica	0,217	0,158	0,177	0,179	0,177	0,249	0,223	0,187	0,176	0,246	0,229	0,251	0,239	0,278
Côte d'Ivoire	0,234	0,234	0,179	0,186	0,166	0,162	0,163	0,149	0,142	0,156	0,147	0,150	0,142	0,134
Croatia	0,216	0,231	0,218	0,192	0,232	0,215	0,204	0,185	0,171	0,154	0,164	0,156	0,153	0,162
Dominican Rep.	0,499	0,614	0,540	0,437	0,346	0,383	0,436	0,494	0,521	0,509	0,494	0,452	0,457	0,489
Ecuador	0,101	0,115	0,108	0,127	0,134	0,147	0,139	0,160	0,179	0,187	0,205	0,218	0,231	0,238
Egypt	0,111	0,145	0,140	0,161	0,186	0,213	0,233	0,244	0,267	0,286	0,345	0,372	0,375	0,378
El Salvador	0,408	0,472	0,447	0,472	0,505	0,489	0,430	0,461	0,415	0,428	0,433	0,363	0,309	0,385
Ethiopia	0,449	0,384	0,423	0,409	0,361	0,412	0,458	0,488	0,434	0,697	0,621	0,754	0,776	0,776
Georgia	0,393	0,375	0,373	0,370	0,310	0,345	0,259	0,248	0,265	0,274	0,371	0,410	0,392	0,333
Guatemala	0,188	0,201	0,180	0,179	0,212	0,195	0,212	0,193	0,186	0,167	0,144	0,131	0,153	0,141
Haiti	0,593	0,541	0,482	0,218	0,258	0,168	0,163	0,164	0,423	0,483	0,442	0,535	0,595	0,627
Honduras	0,235	0,227	0,221	0,186	0,152	0,165	0,154	0,156	0,149	0,140	0,143	0,183	0,188	0,193
India	0,200	0,189	0,163	0,189	0,159	0,159	0,124	0,139	0,131	0,120	0,164	0,194	0,163	0,220
Indonesia	0,112	0,119	0,128	0,126	0,128	0,144	0,160	0,167	0,186	0,206	0,175	0,180	0,206	0,248
Iran	0,076	0,090	0,187	0,099	0,111	0,115	0,116	0,132	0,131	0,137	0,152	0,204	0,219	0,219
Israel	0,111	0,134	0,130	0,158	0,169	0,163	0,163	0,164	0,183	0,196	0,143	0,150	0,184	0,168
Japan	0,148	0,142	0,155	0,152	0,145	0,145	0,144	0,144	0,142	0,138	0,143	0,146	0,139	0,145
Jordan	0,137	0,145	0,161	0,215	0,227	0,198	0,195	0,206	0,209	0,195	0,195	0,253	0,227	0,237
Kazakhstan	0,134	0,211	0,215	0,347	0,319	0,211	0,212	0,251	0,408	0,396	0,403	0,464	0,398	0,556
Kenya	0,140	0,145	0,161	0,178	0,179	0,178	0,190	0,242	0,253	0,299	0,355	0,323	0,263	0,246
Lao People's Dem. Rep.	0,416	0,355	0,206	0,159	0,144	0,140	0,123	0,121	0,118	0,150	0,149	0,145	0,192	0,132
Lebanon	0,142	0,149	0,151	0,187	0,199	0,194	0,202	0,194	0,204	0,212	0,227	0,225	0,255	0,274
Madagascar	0,183	0,197	0,204	0,193	0,201	0,217	0,222	0,242	0,224	0,240	0,223	0,229	0,223	0,199

Malaysia	0,116	0,090	0,077	0,115	0,134	0,179	0,190	0,189	0,167	0,157	0,189	0,159	0,137	0,156
Mali	0,730	0,720	0,461	0,712	0,703	0,697	0,683	0,679	0,524	0,545	0,524	0,423	0,498	0,495
Mauritius	0,198	0,151	0,192	0,223	0,217	0,220	0,213	0,206	0,199	0,170	0,192	0,191	0,133	0,143
Mexico	0,426	0,444	0,380	0,399	0,380	0,328	0,324	0,320	0,309	0,289	0,284	0,284	0,282	0,274
Mongolia	0,690	0,582	0,418	0,320	0,383	0,360	0,417	0,348	0,342	0,326	0,431	0,527	0,487	0,626
Morocco	0,112	0,107	0,113	0,110	0,112	0,116	0,119	0,122	0,124	0,126	0,128	0,137	0,141	0,159
Myanmar	0,407	0,473	0,453	0,332	0,386	0,418	0,418	0,640	0,687	0,721	0,739	0,636	0,574	0,721
Nepal	0,438	0,385	0,395	0,419	0,407	0,359	0,355	0,385	0,395	0,376	0,417	0,427	0,401	0,440
New Zealand	0,089	0,118	0,113	0,118	0,139	0,154	0,156	0,151	0,146	0,142	0,146	0,158	0,144	0,152
Nicaragua	0,169	0,173	0,176	0,153	0,157	0,208	0,224	0,231	0,276	0,296	0,276	0,270	0,282	0,293
Nigeria	0,188	0,164	0,215	0,248	0,366	0,311	0,289	0,385	0,336	0,326	0,359	0,193	0,173	0,281
North Macedonia	0,131	0,134	0,136	0,127	0,130	0,128	0,124	0,120	0,112	0,124	0,108	0,105	0,106	0,103
Norway	0,060	0,064	0,059	0,065	0,066	0,063	0,066	0,066	0,069	0,064	0,069	0,074	0,067	0,075
Pakistan	0,141	0,173	0,165	0,168	0,218	0,209	0,224	0,198	0,178	0,195	0,144	0,126	0,136	0,179
Peru	0,192	0,186	0,193	0,212	0,203	0,213	0,211	0,206	0,207	0,220	0,227	0,214	0,226	0,263
Philippines	0,108	0,148	0,148	0,156	0,168	0,181	0,181	0,185	0,202	0,226	0,272	0,228	0,236	0,266
Rep. of Korea	0,204	0,187	0,185	0,190	0,194	0,194	0,188	0,184	0,172	0,187	0,188	0,197	0,194	0,225
Rep. of Moldova	0,173	0,174	0,159	0,142	0,138	0,159	0,165	0,170	0,171	0,151	0,145	0,141	0,147	0,158
Russian Federation	0,137	0,157	0,124	0,115	0,114	0,110	0,123	0,128	0,139	0,144	0,153	0,164	0,200	0,340
Saudi Arabia	0,120	0,125	0,126	0,130	0,122	0,141	0,145	0,158	0,191	0,204	0,206	0,224	0,246	0,237
Serbia	0,186	0,146	0,152	0,144	0,159	0,152	0,156	0,163	0,161	0,151	0,154	0,158	0,152	0,148
Singapore	0,112	0,115	0,127	0,104	0,109	0,100	0,094	0,091	0,080	0,086	0,245	0,270	0,189	0,125
South Africa	0,134	0,142	0,156	0,145	0,157	0,173	0,167	0,175	0,199	0,222	0,216	0,220	0,258	0,255
Sri Lanka	0,129	0,151	0,168	0,186	0,193	0,198	0,211	0,221	0,226	0,230	0,223	0,234	0,219	0,223
Switzerland	0,190	0,192	0,161	0,162	0,152	0,139	0,148	0,142	0,129	0,126	0,124	0,130	0,121	0,131
Syria	0,132	0,202	0,248	0,320	0,379	0,366	0,452	0,432	0,464	0,473	0,443	0,279	0,251	0,361
Tajikistan	0,829	0,907	0,905	0,809	0,279	0,338	0,287	0,281	0,291	0,348	0,340	0,391	0,438	0,385
Thailand	0,120	0,116	0,116	0,117	0,117	0,119	0,135	0,131	0,136	0,155	0,177	0,170	0,171	0,194
Tunisia	0,145	0,125	0,120	0,120	0,119	0,121	0,120	0,118	0,113	0,115	0,114	0,112	0,109	0,108
Türkiye	0,062	0,077	0,070	0,070	0,074	0,068	0,069	0,065	0,063	0,068	0,060	0,058	0,068	0,063
Uganda	0,182	0,188	0,200	0,223	0,237	0,283	0,312	0,323	0,340	0,394	0,492	0,519	0,392	0,504
Ukraine	0,081	0,080	0,083	0,100	0,093	0,087	0,097	0,091	0,114	0,102	0,104	0,112	0,111	0,150
United Arab Emirates	0,178	0,196	0,164	0,209	0,196	0,184	0,179	0,171	0,149	0,179	0,153	0,195	0,199	0,174
United Kingdom	0,063	0,065	0,065	0,064	0,069	0,071	0,069	0,067	0,067	0,071	0,068	0,075	0,076	0,065
United Rep. of Tanzania	0,290	0,266	0,247	0,325	0,261	0,313	0,394	0,364	0,344	0,357	0,330	0,276	0,315	0,369
Uruguay	0,147	0,122	0,168	0,184	0,180	0,187	0,178	0,163	0,164	0,153	0,154	0,145	0,124	0,138
USA	0,085	0,087	0,092	0,097	0,098	0,103	0,107	0,106	0,111	0,077	0,074	0,071	0,068	0,082
Uzbekistan	0,259	0,186	0,209	0,263	0,406	0,463	0,474	0,398	0,387	0,346	0,298	0,345	0,339	0,360
Viet Nam	0,168	0,165	0,188	0,200	0,209	0,221	0,218	0,207	0,225	0,254	0,261	0,254	0,242	0,268
Zimbabwe	0,139	0,158	0,142	0,124	0,196	0,199	0,239	0,212	0,277	0,248	0,249	0,247	0,307	0,259

Source: Author's own calculation using Stata. Data: UN Comtrade

Table 4: Country-level annual FTR, 2010–2023

COUNTRY	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Albania	0,500	0,500	0,500	0,500	0,400	0,400	0,500	0,400	0,500	0,500	0,500	0,500	0,400	0,400
Argentina	0,600	0,700	0,700	0,700	0,600	0,600	0,700	0,600	0,600	0,600	0,600	0,600	0,600	0,600
Armenia	0,400	0,500	0,400	0,400	0,400	0,400	0,500	0,400	0,500	0,500	0,500	0,500	0,500	0,500
Australia	0,900	0,900	0,900	1,000	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900
Bahrain	0,500	0,600	0,600	0,600	0,600	0,600	0,600	0,500	0,600	0,600	0,600	0,600	0,600	0,600
Bangladesh	0,300	0,400	0,400	0,300	0,300	0,300	0,400	0,300	0,400	0,400	0,400	0,300	0,400	0,400
Belarus	0,600	0,600	0,600	0,600	0,500	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600
Bolivia (Plurinational State of)	0,400	0,400	0,500	0,400	0,300	0,300	0,400	0,300	0,400	0,400	0,400	0,400	0,400	0,400
Bosnia Herzegovina	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500	0,500
Brazil	0,700	0,700	0,700	0,700	0,700	0,700	0,800	0,700	0,700	0,700	0,700	0,700	0,700	0,700
Burkina Faso	0,200	0,300	0,300	0,200	0,200	0,100	0,200	0,100	0,200	0,200	0,200	0,200	0,200	0,200
Cabo Verde	0,400	0,400	0,400	0,400	0,400	0,400	0,500	0,400	0,400	0,400	0,400	0,300	0,300	0,300
Cambodia	0,200	0,300	0,300	0,300	0,300	0,300	0,400	0,300	0,400	0,400	0,400	0,400	0,400	0,400
Cameroon	0,300	0,400	0,300	0,300	0,300	0,300	0,400	0,300	0,400	0,300	0,300	0,300	0,300	0,300
Canada	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900
Chile	0,700	0,700	0,700	0,700	0,600	0,700	0,700	0,600	0,700	0,700	0,700	0,700	0,700	0,700
China	0,800	0,800	0,900	0,800	0,800	0,800	0,900	0,800	0,800	0,800	0,800	0,800	0,800	0,800
China, Hong Kong SAR	0,800	0,800	0,900	0,800	0,800	0,800	0,900	0,800	0,800	0,800	0,800	0,800	0,800	0,800
China, Macao SAR	0,800	0,800	0,900	0,800	0,800	0,800	0,900	0,800	0,800	0,800	0,800	0,800	0,800	0,800
Colombia	0,600	0,600	0,600	0,600	0,600	0,600	0,700	0,600	0,600	0,600	0,600	0,600	0,600	0,600
Costa Rica	0,600	0,600	0,600	0,600	0,600	0,500	0,600	0,500	0,600	0,600	0,600	0,600	0,600	0,600
Côte d'Ivoire	0,300	0,300	0,300	0,200	0,200	0,200	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300
Croatia	0,700	0,700	0,700	0,600	0,600	0,600	0,700	0,600	0,700	0,700	0,700	0,700	0,600	0,600
Dominican Rep.	0,400	0,500	0,500	0,400	0,400	0,400	0,500	0,400	0,500	0,500	0,500	0,400	0,400	0,400
Ecuador	0,400	0,500	0,500	0,500	0,400	0,400	0,500	0,400	0,500	0,500	0,500	0,400	0,400	0,400
Egypt	0,500	0,500	0,500	0,500	0,500	0,500	0,600	0,500	0,500	0,500	0,500	0,500	0,500	0,500
El Salvador	0,400	0,400	0,400	0,400	0,300	0,300	0,400	0,400	0,400	0,400	0,400	0,400	0,400	0,400
Ethiopia	0,200	0,200	0,300	0,200	0,200	0,200	0,300	0,200	0,300	0,200	0,200	0,200	0,200	0,200
Georgia	0,500	0,500	0,500	0,500	0,500	0,500	0,600	0,500	0,500	0,600	0,600	0,500	0,500	0,500
Guatemala	0,400	0,400	0,400	0,400	0,300	0,300	0,400	0,400	0,400	0,400	0,400	0,300	0,400	0,400
Haiti	0,300	0,300	0,300	0,200	0,100	0,100	0,300	0,200	0,300	0,300	0,200	0,200	0,200	0,200
Honduras	0,300	0,400	0,300	0,300	0,200	0,300	0,400	0,300	0,400	0,300	0,400	0,300	0,300	0,300
India	0,600	0,700	0,700	0,700	0,600	0,600	0,700	0,600	0,700	0,700	0,700	0,700	0,700	0,700
Indonesia	0,500	0,500	0,500	0,500	0,400	0,500	0,600	0,500	0,600	0,500	0,500	0,500	0,500	0,500
Iran	0,500	0,500	0,500	0,500	0,400	0,500	0,600	0,500	0,500	0,600	0,600	0,500	0,600	0,500
Israel	0,800	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900
Japan	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,800
Jordan	0,500	0,600	0,500	0,500	0,500	0,400	0,600	0,500	0,600	0,600	0,600	0,500	0,500	0,600
Kazakhstan	0,500	0,600	0,600	0,600	0,500	0,500	0,600	0,600	0,600	0,600	0,600	0,500	0,600	0,600
Kenya	0,400	0,400	0,400	0,300	0,300	0,400	0,500	0,400	0,400	0,400	0,400	0,400	0,400	0,400
Lao People's Dem. Rep.	0,300	0,300	0,300	0,300	0,200	0,300	0,400	0,300	0,400	0,400	0,400	0,400	0,300	0,300
Lebanon	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,500	0,600	0,600	0,500	0,500	0,500	0,500
Madagascar	0,300	0,300	0,300	0,300	0,200	0,200	0,300	0,200	0,300	0,300	0,300	0,200	0,200	0,200

Malaysia	0,700	0,700	0,700	0,700	0,600	0,700	0,700	0,700	0,700	0,800	0,800	0,800	0,800	0,700
Mali	0,300	0,300	0,300	0,300	0,200	0,200	0,300	0,200	0,300	0,200	0,300	0,200	0,200	0,200
Mauritius	0,500	0,500	0,500	0,500	0,500	0,500	0,600	0,500	0,600	0,600	0,600	0,600	0,500	0,500
Mexico	0,600	0,700	0,600	0,700	0,600	0,600	0,700	0,700	0,700	0,700	0,700	0,600	0,600	0,600
Mongolia	0,400	0,400	0,400	0,400	0,400	0,300	0,500	0,400	0,400	0,400	0,400	0,400	0,500	0,400
Morocco	0,500	0,500	0,600	0,500	0,500	0,500	0,600	0,500	0,600	0,600	0,600	0,600	0,600	0,600
Myanmar	0,100	0,200	0,200	0,200	0,100	0,200	0,300	0,300	0,400	0,400	0,400	0,300	0,300	0,300
Nepal	0,400	0,400	0,400	0,400	0,300	0,300	0,400	0,300	0,500	0,400	0,400	0,400	0,400	0,400
New Zealand	0,800	0,900	0,900	0,900	0,800	0,800	0,900	0,800	0,800	0,800	0,800	0,800	0,800	0,800
Nicaragua	0,300	0,300	0,300	0,300	0,200	0,200	0,400	0,300	0,400	0,400	0,400	0,300	0,400	0,300
Nigeria	0,400	0,400	0,400	0,400	0,300	0,300	0,400	0,300	0,400	0,400	0,400	0,400	0,400	0,400
North Macedonia	0,600	0,600	0,600	0,600	0,500	0,500	0,600	0,500	0,600	0,600	0,500	0,500	0,600	0,600
Norway	0,800	0,800	0,900	0,800	0,800	0,800	0,900	0,900	0,900	0,900	0,900	0,900	0,900	0,900
Pakistan	0,400	0,400	0,400	0,300	0,300	0,200	0,400	0,300	0,300	0,300	0,300	0,300	0,300	0,300
Peru	0,400	0,500	0,500	0,500	0,400	0,400	0,500	0,400	0,500	0,500	0,500	0,500	0,500	0,500
Philippines	0,600	0,600	0,600	0,600	0,600	0,600	0,700	0,600	0,600	0,600	0,600	0,600	0,600	0,600
Rep. of Korea	0,900	1,000	1,000	1,000	0,900	0,900	1,000	0,900	0,900	0,900	0,900	0,900	0,900	0,900
Rep. of Moldova	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,500	0,500	0,500	0,600	0,500	0,500	0,500
Russian Federation	0,700	0,800	0,800	0,800	0,800	0,800	0,800	0,800	0,800	0,800	0,800	0,800	0,800	0,800
Saudi Arabia	0,600	0,600	0,600	0,600	0,600	0,600	0,700	0,600	0,600	0,600	0,700	0,700	0,700	0,700
Serbia	0,600	0,700	0,700	0,700	0,600	0,600	0,700	0,700	0,700	0,700	0,700	0,600	0,700	0,700
Singapore	0,900	0,900	0,900	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0,900	0,900	1,000	0,900
South Africa	0,600	0,600	0,600	0,700	0,600	0,600	0,700	0,600	0,700	0,700	0,700	0,700	0,700	0,600
Sri Lanka	0,400	0,500	0,500	0,400	0,400	0,400	0,500	0,400	0,500	0,500	0,500	0,500	0,500	0,500
Switzerland	0,900	0,900	0,900	0,900	0,900	0,900	0,900	1,000	1,000	1,000	1,000	0,900	0,900	0,900
Syria	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300	0,300
Tajikistan	0,300	0,400	0,300	0,300	0,200	0,200	0,300	0,200	0,200	0,200	0,200	0,200	0,200	0,200
Thailand	0,700	0,700	0,700	0,700	0,600	0,700	0,700	0,700	0,700	0,700	0,700	0,700	0,700	0,700
Tunisia	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,500	0,600	0,500
Türkiye	0,700	0,600	0,600	0,600	0,600	0,600	0,700	0,700	0,700	0,700	0,700	0,700	0,700	0,700
Uganda	0,300	0,300	0,300	0,300	0,200	0,200	0,300	0,200	0,300	0,200	0,200	0,200	0,200	0,200
Ukraine	0,700	0,700	0,700	0,700	0,700	0,700	0,700	0,600	0,700	0,600	0,600	0,600	0,600	0,600
United Arab Emirates	0,600	0,600	0,600	0,600	0,600	0,600	0,700	0,600	0,700	0,700	0,800	0,800	0,700	0,700
United Kingdom	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0,900	0,900	1,000	1,000
United Rep. of Tanzania	0,300	0,300	0,300	0,200	0,200	0,200	0,300	0,200	0,300	0,200	0,200	0,200	0,200	0,200
Uruguay	0,500	0,500	0,600	0,500	0,500	0,500	0,500	0,500	0,600	0,600	0,600	0,600	0,700	0,700
USA	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Uzbekistan	0,400	0,400	0,400	0,400	0,300	0,300	0,400	0,300	0,400	0,400	0,500	0,400	0,500	0,500
Viet Nam	0,500	0,600	0,600	0,500	0,500	0,500	0,600	0,600	0,600	0,600	0,600	0,600	0,600	0,600
Zimbabwe	0,300	0,300	0,300	0,300	0,200	0,200	0,300	0,300	0,300	0,300	0,300	0,200	0,200	0,200

<u>*Source:*</u> Computed by the author for the purpose of this thesis. <u>Data:</u> UNCTAD.

Table 5: Country-level annual RQ (normalized), 2010–2023

COUNTRY	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Albania	0,107	0,054	-0,084	-0,064	0,057	0,044	0,064	0,111	0,114	0,092	-0,020	-0,005	0,016	0,063
Argentina	-0,758	-0,707	-0,841	-0,835	-1,013	-0,797	-0,253	-0,120	-0,190	-0,449	-0,547	-0,584	-0,579	-0,507
Armenia	0,384	0,371	0,408	0,344	0,123	0,213	0,242	0,266	0,285	0,258	0,208	0,197	0,078	0,096
Australia	1,684	1,840	1,930	1,881	1,747	1,740	1,814	1,826	1,828	1,847	1,768	1,786	1,800	1,813
Bahrain	0,882	0,900	0,803	0,820	0,627	0,737	0,534	0,496	0,496	0,520	0,555	0,796	0,870	0,910
Bangladesh	-0,837	-0,827	-0,979	-0,949	-0,896	-0,777	-0,759	-0,743	-0,785	-0,890	-0,894	-0,871	-0,924	-0,901
Belarus	-1,171	-1,332	-1,030	-1,036	-0,895	-1,003	-0,914	-0,882	-0,788	-0,508	-0,683	-0,794	-1,076	-1,175
Bolivia (Plurinational State of)	-0,839	-0,800	-0,869	-0,857	-0,842	-0,821	-0,839	-0,829	-0,849	-0,976	-1,051	-1,117	-1,137	-1,159
Bosnia Herzegovina	-0,241	-0,272	-0,205	-0,201	-0,186	-0,251	-0,244	-0,168	-0,316	-0,377	-0,374	-0,380	-0,380	-0,348
Brazil	0,190	0,189	0,189	0,130	-0,036	-0,096	-0,096	-0,106	-0,244	-0,099	-0,152	-0,151	-0,199	-0,236
Burkina Faso	-0,158	-0,193	-0,247	-0,264	-0,353	-0,419	-0,425	-0,416	-0,424	-0,468	-0,499	-0,459	-0,498	-0,482
Cabo Verde	-0,120	-0,008	-0,034	-0,182	-0,196	-0,213	-0,182	-0,139	-0,207	-0,054	0,002	0,066	0,097	0,097
Cambodia	-0,412	-0,661	-0,517	-0,491	-0,612	-0,633	-0,567	-0,604	-0,591	-0,649	-0,696	-0,689	-0,695	-0,676
Cameroon	-0,750	-0,815	-0,903	-0,919	-0,808	-0,759	-0,714	-0,791	-0,775	-0,773	-0,746	-0,817	-0,755	-0,739
Canada	1,633	1,599	1,728	1,753	1,682	1,659	1,771	1,844	1,642	1,683	1,593	1,632	1,632	1,572
Chile	1,468	1,489	1,547	1,501	1,324	1,223	1,276	1,240	1,175	1,077	0,890	0,874	0,828	0,847
China	-0,128	-0,099	-0,249	-0,263	-0,169	-0,179	-0,148	-0,071	-0,091	-0,062	-0,067	-0,025	-0,091	-0,082
China, Hong Kong SAR	2,014	1,812	1,999	1,968	1,990	2,175	2,231	2,192	2,214	2,035	1,852	1,746	1,724	1,731
China, Macao SAR	1,434	1,434	1,430	1,429	1,704	1,709	1,617	1,618	1,527	1,528	1,434	1,433	1,431	1,431
Colombia	0,056	0,218	0,222	0,236	0,256	0,309	0,273	0,168	0,109	0,232	0,161	0,237	0,186	0,137
Costa Rica	0,625	0,571	0,686	0,736	0,525	0,617	0,655	0,546	0,651	0,669	0,539	0,561	0,592	0,575
Côte d'Ivoire	-0,954	-0,942	-0,798	-0,710	-0,549	-0,446	-0,444	-0,405	-0,297	-0,316	-0,321	-0,289	-0,216	-0,189
Croatia	0,313	0,275	0,206	0,226	0,119	0,146	0,180	0,296	0,396	0,385	0,202	0,332	0,299	0,444
Dominican Rep.	-0,066	-0,188	-0,185	-0,174	-0,149	-0,090	-0,065	-0,107	-0,145	-0,102	-0,097	-0,010	-0,060	0,049
Ecuador	-1,256	-1,137	-0,998	-0,830	-0,760	-0,966	-0,867	-0,937	-0,824	-0,732	-0,736	-0,555	-0,478	-0,599
Egypt	-0,085	-0,221	-0,512	-0,739	-0,743	-0,736	-0,767	-0,708	-0,743	-0,703	-0,636	-0,570	-0,669	-0,573
El Salvador	0,486	0,455	0,230	0,235	0,190	0,104	-0,012	-0,063	-0,024	-0,056	-0,075	-0,289	-0,386	-0,319
Ethiopia	-0,721	-0,862	-0,917	-1,068	-0,904	-0,903	-0,961	-0,899	-0,846	-0,828	-0,816	-0,768	-0,782	-0,837
Georgia	0,644	0,716	0,693	0,728	0,820	0,810	0,945	0,942	0,801	0,878	0,806	0,843	0,773	0,809
Guatemala	-0,364	-0,392	-0,465	-0,506	-0,473	-0,405	-0,356	-0,452	-0,391	-0,423	-0,377	-0,386	-0,382	-0,408
Haiti	-1,117	-1,203	-1,226	-1,202	-1,315	-1,334	-1,333	-1,300	-1,242	-1,272	-1,308	-1,416	-1,417	-1,545
Honduras	-0,357	-0,278	-0,381	-0,443	-0,584	-0,530	-0,595	-0,450	-0,479	-0,519	-0,556	-0,607	-0,620	-0,682
India	-0,278	-0,340	-0,374	-0,372	-0,381	-0,330	-0,254	-0,216	-0,156	-0,098	-0,149	-0,170	-0,088	-0,127
Indonesia	-0,146	-0,151	-0,179	-0,049	0,003	-0,139	0,034	0,100	0,073	0,111	0,225	0,342	0,281	0,341
Iran	-1,422	-1,198	-1,249	-1,375	-1,302	-1,091	-1,056	-1,083	-1,293	-1,361	-1,393	-1,394	-1,398	-1,468
Israel	1,055	1,199	1,107	1,085	1,039	1,100	1,241	1,215	1,164	1,242	1,152	1,175	1,122	1,054
Japan	1,197	1,334	1,430	1,359	1,299	1,411	1,529	1,399	1,365	1,389	1,367	1,396	1,411	1,398
Jordan	0,107	0,191	0,182	0,100	0,105	0,168	0,118	0,134	0,085	0,160	0,193	0,192	0,212	0,314
Kazakhstan	-0,359	-0,311	-0,335	-0,337	-0,148	-0,071	-0,135	0,083	0,055	0,113	0,054	0,013	-0,064	0,005
Kenya	-0,353	-0,523	-0,512	-0,506	-0,326	-0,290	-0,227	-0,199	-0,299	-0,344	-0,460	-0,425	-0,391	-0,399
Lao People's Dem. Rep.	-0,948	-0,927	-0,847	-0,809	-0,746	-0,699	-0,665	-0,686	-0,793	-0,721	-0,776	-0,742	-0,819	-0,770
Lebanon	0,012	-0,281	-0,362	-0,289	-0,442	-0,363	-0,416	-0,357	-0,470	-0,561	-0,716	-0,822	-0,943	-0,913
Madagascar	-0,743	-0,743	-0,753	-0,875	-0,893	-0,878	-0,800	-0,794	-0,890	-0,850	-0,871	-0,869	-0,831	-0,850

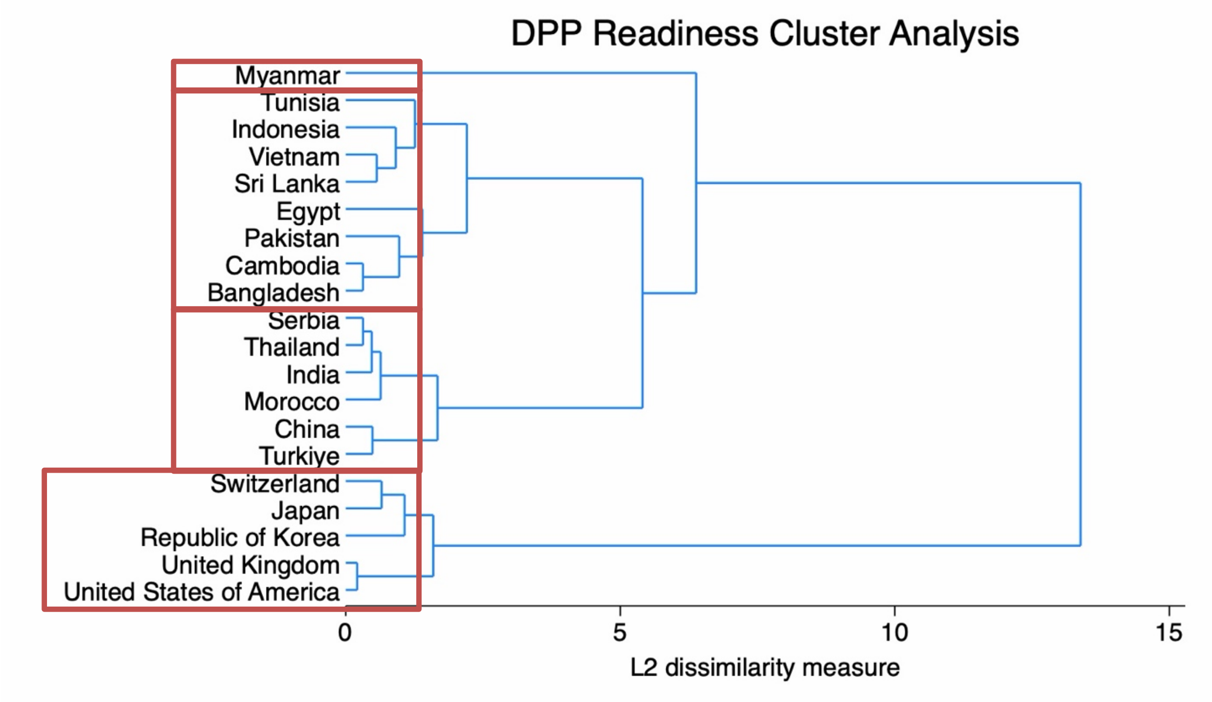
Malaysia	0,654	0,525	0,755	0,845	0,883	0,762	0,729	0,766	0,748	0,756	0,638	0,730	0,656	0,588
Mali	-0,518	-0,471	-0,526	-0,631	-0,648	-0,511	-0,561	-0,565	-0,615	-0,656	-0,729	-0,670	-0,711	-0,744
Mauritius	0,809	0,755	0,969	0,962	1,137	1,013	1,063	1,067	1,041	0,960	0,997	0,938	0,897	0,944
Mexico	0,116	0,173	0,286	0,286	0,208	0,183	0,161	0,164	-0,003	-0,042	-0,120	-0,191	-0,156	-0,176
Mongolia	-0,278	-0,309	-0,383	-0,471	-0,310	-0,304	-0,028	-0,036	0,026	-0,066	-0,134	-0,128	-0,195	-0,041
Morocco	0,024	-0,076	-0,006	0,020	0,050	0,059	0,014	0,004	-0,116	0,027	0,065	-0,075	-0,081	-0,047
Myanmar	-1,675	-1,595	-1,763	-1,458	-1,332	-1,110	-0,882	-0,843	-0,817	-0,850	-0,729	-1,137	-1,260	-1,445
Nepal	-0,836	-0,807	-0,793	-0,814	-0,717	-0,699	-0,648	-0,657	-0,592	-0,573	-0,664	-0,638	-0,597	-0,607
New Zealand	1,718	1,971	1,993	1,927	2,012	2,013	2,059	2,080	1,971	1,971	1,933	1,853	1,860	1,877
Nicaragua	-0,447	-0,451	-0,404	-0,373	-0,402	-0,308	-0,399	-0,497	-0,554	-0,652	-0,681	-0,887	-1,002	-1,013
Nigeria	-0,911	-0,876	-0,753	-0,741	-0,794	-0,740	-0,815	-0,778	-0,830	-0,865	-0,887	-0,873	-0,996	-0,827
North Macedonia	-0,112	-0,087	0,209	0,145	0,280	0,271	0,274	0,343	0,399	0,193	0,303	0,224	0,223	0,202
Norway	1,637	1,795	1,822	1,914	1,766	1,781	1,805	1,838	1,817	1,767	1,698	1,649	1,573	1,635
Pakistan	-0,688	-0,758	-0,808	-0,806	-0,748	-0,686	-0,660	-0,664	-0,662	-0,620	-0,701	-0,654	-0,765	-0,822
Peru	0,310	0,342	0,253	0,234	0,260	0,318	0,322	0,271	0,298	0,345	0,225	0,085	0,072	0,129
Philippines	-0,031	0,012	0,132	0,032	0,060	0,088	0,126	0,137	-0,005	0,059	0,014	0,015	0,005	0,063
Rep. of Korea	0,803	0,931	0,929	1,018	0,994	0,996	0,976	0,959	0,957	0,912	0,908	0,988	1,017	1,000
Rep. of Moldova	-0,201	-0,198	-0,287	-0,229	-0,136	-0,199	-0,232	-0,122	-0,186	-0,113	-0,152	-0,086	-0,044	-0,055
Russian Federation	-0,362	-0,381	-0,432	-0,406	-0,450	-0,516	-0,424	-0,397	-0,358	-0,354	-0,445	-0,372	-0,892	-0,889
Saudi Arabia	0,348	0,394	0,239	0,272	0,195	0,237	0,188	0,100	0,081	0,179	0,173	0,388	0,554	0,610
Serbia	-0,282	-0,278	-0,277	-0,248	0,002	0,077	-0,009	0,018	0,090	0,064	0,065	0,056	0,089	0,085
Singapore	2,005	1,945	2,125	2,088	2,161	2,230	2,198	2,149	2,137	2,181	2,122	2,135	2,049	2,130
South Africa	0,703	0,655	0,642	0,625	0,402	0,295	0,261	0,230	0,069	0,119	0,090	0,018	-0,062	-0,062
Sri Lanka	-0,075	0,021	0,007	-0,076	-0,006	0,031	-0,045	-0,117	-0,190	-0,186	-0,112	-0,163	-0,457	-0,380
Switzerland	1,740	1,746	1,849	1,797	1,914	1,796	1,919	1,907	1,805	1,767	1,643	1,760	1,762	1,805
Syria	-0,745	-0,838	-1,424	-1,526	-1,637	-1,550	-1,636	-1,639	-1,548	-1,597	-1,648	-1,755	-1,892	-1,892
Tajikistan	-0,997	-0,993	-0,952	-0,962	-0,941	-0,922	-0,955	-0,791	-0,770	-0,801	-0,808	-0,841	-0,842	-0,842
Thailand	0,174	0,183	0,081	0,132	0,160	0,207	0,170	0,210	0,145	0,091	0,086	0,103	0,114	0,119
Tunisia	0,024	-0,217	-0,170	-0,232	-0,353	-0,376	-0,426	-0,120	-0,117	-0,144	-0,110	-0,199	-0,334	-0,434
Türkiye	0,374	0,382	0,471	0,479	0,369	0,217	0,154	0,144	0,052	-0,016	-0,165	-0,123	-0,229	-0,211
Uganda	-0,289	-0,337	-0,424	-0,439	-0,408	-0,384	-0,394	-0,374	-0,401	-0,476	-0,495	-0,479	-0,476	-0,500
Ukraine	-0,582	-0,794	-0,692	-0,666	-0,623	-0,617	-0,523	-0,368	-0,351	-0,290	-0,350	-0,359	-0,412	-0,378
United Arab Emirates	0,740	0,890	0,846	0,990	1,074	1,179	1,078	1,111	1,079	1,146	1,066	1,061	1,058	1,105
United Kingdom	1,546	1,567	1,645	1,728	1,733	1,814	1,681	1,669	1,675	1,713	1,601	1,601	1,649	1,589
United Rep. of Tanzania	-0,420	-0,434	-0,485	-0,435	-0,423	-0,435	-0,413	-0,555	-0,647	-0,693	-0,724	-0,675	-0,611	-0,591
Uruguay	0,553	0,534	0,673	0,757	0,721	0,654	0,736	0,697	0,600	0,629	0,699	0,733	0,725	0,738
USA	1,352	1,397	1,442	1,391	1,286	1,292	1,408	1,509	1,484	1,368	1,278	1,464	1,459	1,431
Uzbekistan	-1,505	-1,581	-1,448	-1,447	-1,467	-1,435	-1,400	-1,293	-1,148	-0,922	-1,022	-0,694	-0,648	-0,672
Viet Nam	-0,543	-0,492	-0,634	-0,600	-0,487	-0,329	-0,312	-0,274	-0,292	-0,278	-0,236	-0,345	-0,347	-0,279
Zimbabwe	-1,767	-1,720	-1,679	-1,687	-1,708	-1,407	-1,473	-1,393	-1,367	-1,300	-1,330	-1,325	-1,331	-1,228

Source: Computed by the author for the purpose of this thesis. Data: World Bank.

4.1.3 Cluster analysis

To address the question of how major textile exporters to the EU cluster into distinct readiness profiles across digital capacity (FTR), regulatory conditions (RQ), and supply chain concentration (HHI), a cluster analysis was performed on the 20 largest textile exporters to the EU. This approach enables the grouping of countries based on their similarity across these three dimensions of readiness. To objectively categorize the sample countries into distinct readiness profiles without introducing arbitrary human weights, an agglomerative hierarchical cluster analysis was conducted. The clustering execution utilized Ward's minimum-variance linkage method computed over-score normalized values to prevent variable scale bias, measured through squared Euclidean distance (L_2 dissimilarity measure). All variables were standardized (z-scores) prior to clustering to ensure comparability across differing scales. The values used were those of 2023. To verify the mathematical validity of the resulting partitions, the *Calinski-Harabasz* pseudo-F stopping rule was executed across a cluster range of $k = 2$ through $k = 5$ (Everitt, 2011). The *Calinski-Harabasz* diagnostic reaches a definitive peak at **4 clusters**, confirming that a four-tiered division maximizes between-cluster variance while minimizing within-cluster variance.

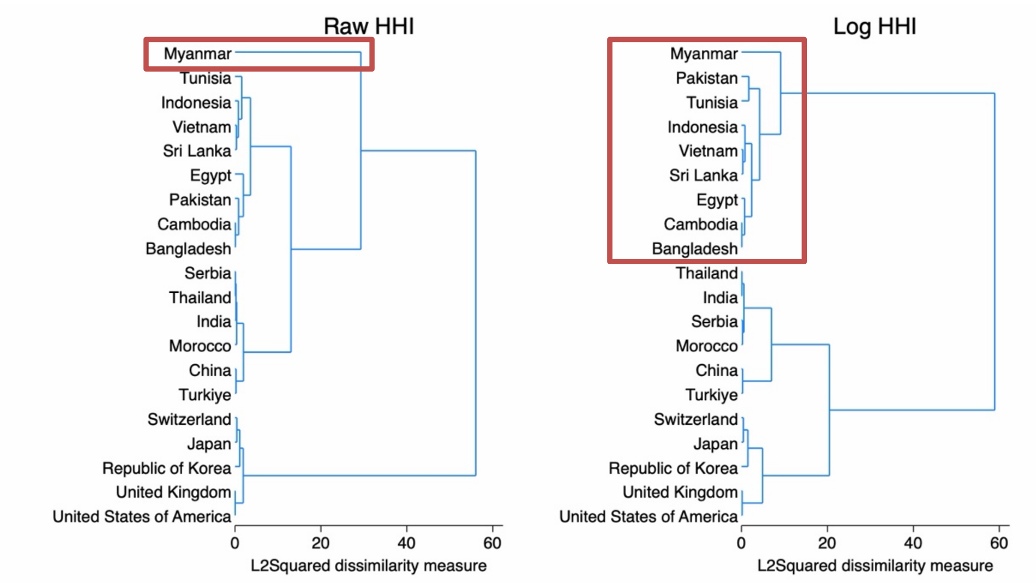
Figure 4: Dendogram of the cluster analysis (for 2023)



<u>*Source:*</u> Author's calculation using Stata. <u>Data:</u> UN Comtrade, UNCTAD and World Bank.

When looking at the standardized HHI variable, it showed that Myanmar stands out as a clear outlier (HHI_{2023} = 0.721, with a z-score exceeding +2 standard deviations from the mean). Since Ward's method based on squared Euclidean distance is sensitive to extreme values, there was a concern that Myanmar's position in the clustering results might be driven more by the scale of the HHI variable than by its overall readiness profile. To test the robustness of the results, two hierarchical clustering models were estimated and compared: one using the raw standardized HHI (together with FTR and RQ), and another using a log-transformed HHI (ln(HHI), also standardized). The results showed a noticeable difference in Myanmar's placement, as can be seen in *Figure 5*. In the raw HHI specification, Myanmar formed its own single-country cluster and only joined the rest of the sample at a very high dissimilarity level, indicating strong outlier behaviour. In contrast, when using the log-transformed HHI, Myanmar clustered more naturally with Pakistan and Tunisia at a relatively low dissimilarity level, aligning with the broader group of developing economies. The separation between advanced economies and developing economies, as well as the internal grouping patterns remained stable across both specifications. Overall, this suggests that Myanmar's outlier status in the baseline model is largely driven by the influence of the raw HHI scale on the distance calculations rather than a fundamentally distinct readiness profile. For this reason, the log-transformed HHI specification was adopted, as it better reflects relative differences in concentration without allowing extreme values to disproportionately influence the clustering results.

Figure 5: Dendogram of the cluster analysis raw and log (for 2023)



<u>*Source:*</u> Author's calculation using Stata. <u>Data:</u> UN Comtrade, UNCTAD and World Bank.

The Calinski–Harabasz pseudo-F statistic was again used to assess clustering solutions ranging from 2 to 5 clusters based on the log-transformed specification. As also evident on the dendogram, the optimal solution is obtained with three clusters. The detailed calculations are provided in Appendix 1. This three-cluster structure provides a clear and theoretically meaningful classification of DPP readiness into advanced, transitioning, and emerging economies. The details of the means of each group can also be found in Appendix 1 for both cluster analyses. The 3-cluster solution based on the log-transformed HHI specification yields the following groups:

Group 1 — Advanced economies: United States, United Kingdom, Republic of Korea, Japan, Switzerland. This group shows substantially above-average regulatory quality (RQ_z = 1.495) and digital trade readiness (FTR_z = 1.295), while also displaying below-average supply chain concentration ($Log(HHI)_z$ = -0.621).

Group 2 — Mid-tier/Transitioning economies: Turkiye, China, Morocco, India, Thailand, Serbia. This group is characterized by near-average regulatory and digital readiness (RQ_z = -0.147; FTR_z = 0.278) and similarly below-average concentration ($Log(HHI)_z$ = -0.484).

Group 3 — Emerging/Developing economies: Bangladesh, Cambodia, Pakistan, Egypt, Sri Lanka, Vietnam, Indonesia, Tunisia, Myanmar. This groups shows below-average scores for both regulatory quality (RQ_z = -0.733) and digital trade readiness (FTR_z = -0.905), combined with above-average supply chain concentration (Log(HHI) = 0.668).

Overall, the results reveal a clear gradient from economies with high levels of regulatory and digital readiness but diversified import structures, to economies with lower readiness levels but more concentrated import structures. This may facilitate data collection and traceability within supply chains (Langley et al., 2023). Notably, Myanmar is now grouped with other emerging economies rather than appearing as a statistical outlier, supporting the robustness of this classification once the HHI outlier issue was addressed.

4.2 Econometric analysis

To examine the extent to which technological readiness, regulatory quality, and supply chain concentration have influenced exporters' ability to retain market share in the EU textile market between 2005 and 2024, a panel-data approach was employed. As mentioned in the methodology, the dependent variable is the exporter's share of total EU textile imports, measured as a proportion bounded between 0 and 1. The analysis focuses on three dimensions of readiness: technological readiness, measured by the Frontier Technology Readiness (FTR) Index; regulatory readiness, measured using the World Bank Regulatory Quality indicator; and supply chain concentration, measured through the Herfindahl–Hirschman Index (HHI). GDP was included as a control variable to account for differences in economic size across exporting countries. The analysis initially estimated a two-way fixed effects model including both country and year fixed effects. This specification captures how changes in readiness indicators within a country over time are associated with changes in its EU market share while controlling for unobserved country-specific characteristics and common temporal shocks.

However, because market share is a fractional variable bounded between 0 and 1 and heavily concentrated near zero, additional estimations were conducted using fractional response models, which are specifically designed for proportion data (Papke & Wooldridge, 2008). A fractional logit model and a population-averaged fractional logit model estimated through Generalized Estimating Equations (GEE) were therefore employed. Finally, a correlated random effects (Mundlak) specification was estimated as a robustness check to distinguish between within-country and between-country effects. The FTR proved to be highly stable across the sampled years. As a robustness check, fixed broadband subscriptions (per 100 people) from the World Bank was evaluated as an alternative proxy. Nonetheless, because its broader scope diluted the specific concept of technological readiness captured by the FTR, it was excluded. Detailed results of these tests are provided in Appendix 2.

The results provide limited evidence that technological readiness, as measured by the FTR Index, has a statistically significant effect on EU market share retention. Regulatory quality exhibits a positive but generally weak relationship with market share in the linear panel models, while supply chain concentration shows a positive association in several specifications, although statistical significance varies across models. GDP displays mixed effects depending on the estimation method. Overall, the results suggest that differences in technological, regulatory, and supply chain readiness alone do not strongly explain variation in exporters' market share retention in the EU textile market over the study period.

First of all, across all four estimations, the coefficient on FTR consistently fails to reach conventional levels of statistical significance. In the two-way fixed effects model, the FTR coefficient is positive (β= 0.0065, SE = 0.0067, p = 0.331), suggesting that, within a given exporter over time, an improvement in technological readiness is associated with a small increase in EU market share, but this relationship is not distinguishable from zero. The 95% confidence interval (-0.0067 to 0.0198) spans both negative and positive values, reinforcing the lack of a robust within-country effect. The population-averaged fractional logit model estimated via GEE produces a notably larger, positive coefficient for FTR (β = 2.293, SE = 2.443, p = 0.348). While this coefficient is an order of magnitude larger than in the linear specifications (a function of the logit transformation rather than a directly comparable marginal effect), the associated standard error is also substantially larger, and the result remains far from conventional significance thresholds (95% CI: -2.496 to 7.082). This indicates considerable uncertainty in the population-averaged relationship between technological readiness and market share once the correlation structure across observations is treated as independent rather than exploiting within-country variation.

The Mundlak (correlated random effects) specification decomposes the FTR effect into within-country and between-country components. The within-country effect (FTR coefficient = 0.0051, SE = 0.0037, p = 0.165) is positive and closer to significance than in the two-way fixed effects model, but still falls short of the 10% threshold. The between-country effect, captured by *mean_FTR* (β = 0.0120, SE = 0.0420, p = 0.775), is also positive but imprecisely estimated and not statistically significant. The similarity in sign but difference in magnitude between the within (0.0051) and between (0.0120) components suggests that, descriptively, countries with persistently higher average technological readiness may have somewhat higher average market shares, but this cross-sectional pattern is not statistically robust. A Hausman-type comparison of the two coefficients would not reject equality given the size of their respective standard errors.

Next, the regulatory quality variable shows a more consistent sign across specifications than FTR, though the pattern of significance differs sharply between the linear and fractional-response models. In the two-way fixed effects model, World Bank regulatory quality carries a positive coefficient (β = 0.0018, SE = 0.0013, p = 0.173), implying that improvements in regulatory quality within a country over time are associated with modest gains in EU market share, though the estimate does not reach conventional significance (95% CI: -0.0008 to 0.0043). The population-averaged fractional logit model (GEE) tells a different story: the coefficient on World Bank regulatory quality is negative and statistically significant (β = -1.247, SE = 0.503, p = 0.013, 95% CI: -2.233 to -0.261). This sign reversal relative to the linear fixed effects model is notable. One interpretation is that once the bounded, skewed nature of market share is properly accounted for via the logit link, and the model is estimated on the population-averaged (rather than within-country) margin, regulatory quality appears to be negatively associated with market share. This possibly reflects that exporters facing tighter, higher-quality regulatory environments at home face compliance costs that offset competitiveness gains. This result could, however, also be driven by between-country composition rather than a genuine within-country effect.

The Mundlak decomposition helps with this discrepancy. The within-country effect (World Bank regulatory quality = 0.0014, SE = 0.0012, $p = 0.237$) is positive but insignificant, consistent with the two-way fixed effects estimate. The between-country effect (*mean_World Bank_regulatory_quality* = -0.0147, SE = 0.0085, $p = 0.084$) is negative and marginally significant at the 10% level. This divergence in sign between the within and between components (+ within, - between) suggests that countries with persistently higher average regulatory quality tend to have somewhat lower average market shares. This is a cross-sectional pattern, possibly reflecting that higher-regulation economies are not the dominant low-cost exporters in this market. While improvements in regulatory quality within a given country over time are mildly, though not significantly, associated with market share gains. The negative GEE coefficient is therefore likely picking up more of this between-country pattern than a true within-country causal effect, since the GEE specification does not partial out unobserved country heterogeneity in the way the fixed effects and Mundlak within estimates do.

Lastly, supply chain concentration, measured by the HHI, displays a similar pattern of sign instability across the tests. In the two-way fixed effects model, the HHI coefficient is positive ($\beta = 0.0063$, SE = 0.0038, $p = 0.100$), narrowly missing significance at the 10% level (95% CI: -0.0012 to 0.0139), and suggesting that increases in supply chain concentration within a country over time are weakly associated with higher EU market share. In the GEE fractional logit model, however, the HHI coefficient is negative and falls short of conventional significance ($\beta = -7.283$, SE = 4.673, $p = 0.119$, 95% CI: -16.442 to 1.875). As with regulatory quality, this represents a sign reversal relative to the linear specification, though here neither estimate reaches significance, so the discrepancy is more a difference in direction of a noisy estimate than a contradiction between a significant and an insignificant result. The Mundlak specification provides the clearest signal for this variable. The within-country effect (HHI = 0.0085, SE = 0.0026, $p = 0.001$) is positive and highly significant, indicating that as supply chain concentration rises within a given exporting country over time, that country's EU market share rises significantly. This is the strongest and most precisely estimated coefficient among the three readiness/concentration variables across all specifications. The between-country effect (*mean_HHI* = -0.0560, SE = 0.0402, p = 0.163) is negative but not statistically significant, again pointing to a within/between divergence similar to that seen for the regulatory index. Countries with persistently higher average concentration are not systematically associated with higher average market share but increases in concentration within a country are.

Table 6: Two-Way Fixed Effects

VARIABLES	(1) Marketshare
FTR	0.00651
	(0.00666)
RQ	0.00177
	(0.00129)
HHI	0.00634
	(0.00381)
GDP	0
	0
Observations	1,162
Number of Countries	83
R-squared	0.268

Note: *Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculation using Stata.*

Table 7: Fractional Logit (GEE)

VARIABLES	(1) Marketshare
FTR	2.293
	(2.443)
RQ	-1.247**
	(0.503)
HHI	-7.283
	(4.673)
GDP	0**
	(0)
Observations	1,162
Number of Countries	83

Note: *Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculation using Stata.*

Table 8: Mundlak (CRE)

VARIABLES	(1) Marketshare
FTR	0.005
	(0.004)
RQ	0.001
	(0.001)
HHI	0.008***
	(0.002)
GDP	-0***
	(0)
mean_FTR	0.01
	(0.04)
mean_RQ	-0.014*
	(0.009)
mean_HHI	-0.056
	(0.040)
mean_GDP	0***
	(0)
Observations	1,162
Number of Countries	83

Note: *Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculation using Stata.*

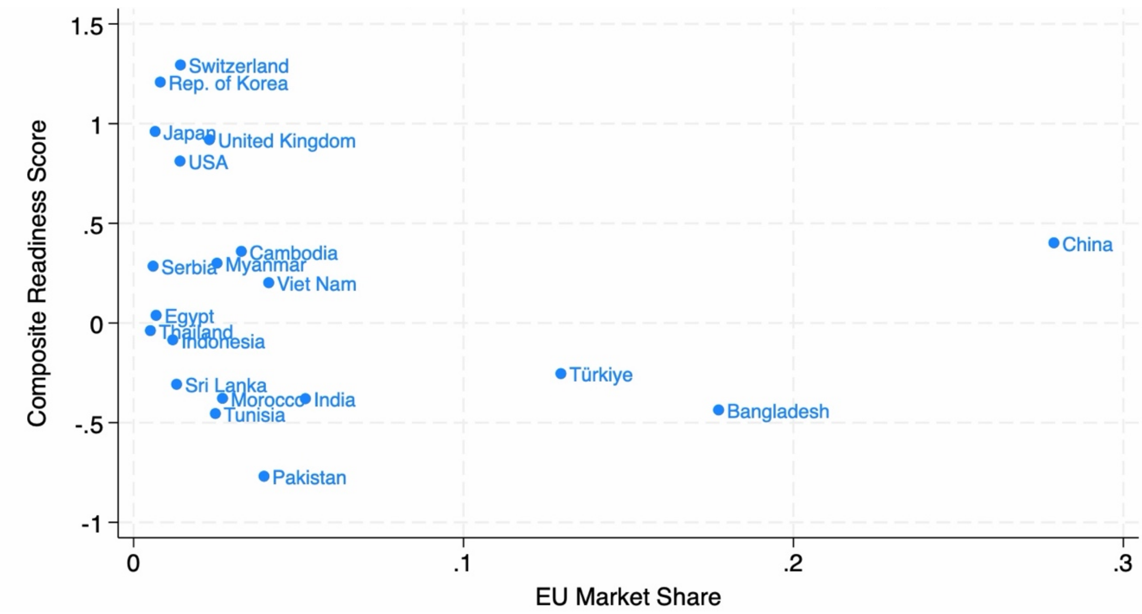
Because raw GDP values are orders of magnitude larger than the other indicators, the marginal effect of a single-dollar change was mathematically negligible, resulting in coefficients that rounded to zero by Stata. In the two-way fixed effects model GDP is not statistically significant, but in the GEE fractional logit specification it is significant at the 5% level. This indicates that despite its negligible-looking coefficient, exporter economic size is robustly associated with EU market share once the nonlinear, bounded nature of the dependent variable is properly modelled. Results were checked for multicollinearity with VIF. Standard errors used were robust to arbitrary heteroskedasticity and within-country serial correlation.

4.3 Exposure-Readiness matrix

Since the Digital Product Passport is not yet in force, the third hypothesis cannot be tested econometrically using historical trade data. Instead, an exposure-readiness matrix was constructed to assess which exporters combine high historical dependence (using EU market share as a proxy) on the EU market with the weakest structural capacity to adapt to DPP requirements, directly addressing sub-question 3. For each of the 20 sample countries, two scores were plotted for 2023. The EU market share was plotted on the x-axis, and a composite readiness score (the standardized average of digital and regulatory readiness) on the y-axis. Median values on both axes divide the matrix into four quadrants, with the bottom-right quadrant being high EU market share combined with low composite readiness. This represents countries at the highest structural risk of exclusion under a stricter compliance regime.

The matrix in *Figure 6* reveals a policy-relevant pattern. China occupies a distinct position with by far the highest EU market share (≈28%) but a moderately positive readiness score (≈0.4), placing it closer to the top-right "resilient dominance" quadrant rather than the high-risk zone. Bangladesh and Türkiye, by contrast, fall squarely into the high-exposure, low-readiness quadrant. Bangladesh combines the second-highest EU market share (≈18%) with one of the lowest composite readiness scores (≈−0.43) in the sample, while Türkiye shows a similar pattern at a smaller scale (≈13% market share, ≈−0.26 readiness). Pakistan records the lowest readiness score of any country in the sample (≈−0.78) alongside a moderate market share (≈4%), placing it at high relative risk despite its smaller absolute trade volume. India, Morocco, Tunisia, and Sri Lanka cluster in a similar low-readiness region, though with smaller EU market shares, indicating elevated but less systemically significant exposure. This pattern stands in sharp contrast to high-income exporters such as Switzerland, the Republic of Korea, Japan, the United Kingdom, and the USA, which occupy the top-left quadrant: minimal EU market share but the highest readiness scores in the sample (0.8–1.3), reflecting mature digital and regulatory infrastructure but limited reliance on EU textile trade.

Figure 6: Exposure-Readiness matrix (2023)



Source: Author's calculation using Stata. Data: UN Comtrade, UNCTAD and World Bank.

5. Discussion

5.1 Interpretation of the results

The empirical analysis was designed to answer the thesis's research question by addressing three interrelated sub-questions: how textile-exporting countries differ in their underlying readiness profiles (H1), whether these readiness dimensions have historically shaped exporters' ability to retain EU market share (H2), and which exporters are most structurally exposed once the Digital Product Passport (DPP) enters into force (H3). Combined, these three analyses offer an exploratory empirical assessment of the challenges textile-exporting countries encounter during DPP implementation.

Table 9: Hypotheses overview

H1	Lower-income countries display systematically weaker digital and regulatory and supply chain readiness than higher-income, lower share competitors.	*Partially confirmed*
H2	Over the last twenty years, countries that improved their digital infrastructure and regulatory systems achieved a statistically significant increase in their share of the EU textile market.	*Not confirmed*
H3	Exporters combining high EU market share with low composite digital, regulatory and supply-chain readiness constitute a structurally vulnerable cohort, exposed to disproportionate risk under a future DPP compliance regime.	*Confirmed*

Source: Computed by the author for the purpose of this thesis.

The cluster analysis (H1) confirms that DPP readiness is not randomly distributed across exporting countries but follows a coherent, three-tiered structure. Advanced economies (the United States, the United Kingdom, the Republic of Korea, Japan, and Switzerland) combine high regulatory quality and digital readiness with diversified, low-concentration supply chains. High regulatory quality and digital readiness will help to comply with DPP obligations (Carvalho et al., 2025; Ducuing & Reich, 2023; Piétron et al., 2023). However, highly diversified supply chains create fragmentation, making it harder to aggregate and verify DPP data (Langley et al., 2023). As these countries mostly export finished products to the EU (55%; HS codes 60-62)[1] or re-export due to logistics (Wang et al., 2010), they will have to track the data from countries with less technological and regulatory capabilities to be able to be compliant to EU markets (Legardeur & Ospital, 2024). As a matter of fact, international trade

[1] Share calculated by the author using Excel. Source: UNComtrade

statistics often show major discrepancies due to "entrepôt trade" and re-exports. Major economic powers (like the US) buy goods from manufacturing hubs (like Bangladesh), mark them up, and re-export them to third-party destinations (like the EU), complicating traditional bilateral trade tracking (Wang et al., 2010).

Emerging and developing economies (including Bangladesh, Cambodia, Pakistan, Egypt, Sri Lanka, Vietnam, Indonesia, Tunisia, and Myanmar) display the opposite profile: weak regulatory and technological infrastructure paired with more concentrated import structures. In textiles, one of the largest stated challenges is integrating and standardizing data from the many firms involved in the value chain (Cruz et al., 2025). For countries with very limited digital and regulatory capabilities this will be difficult, as digital product passports require reliable data systems, interoperable standards, and sustained enforcement across many firms and agencies. The literature shows these are exactly the weak points in early DPP implementation (Al-Sabban et al., 2026; Walden et al., 2021). Finally, a mid-tier group, including Turkiye, China, Morocco, India, Thailand, and Serbia, occupies an intermediate position on nearly every dimension. H1 is therefore partially supported. Theoretically, lower-income countries such as Bangladesh or Pakistan exhibit greater supply-chain readiness due to their less diversified product sourcing.

The panel-data results addressing H2 complicate the readiness narrative considerably. Across the two-way fixed effects, fractional logit (GEE), and Mundlak specifications, technological readiness (FTR) never reaches conventional statistical significance, and its sign, while consistently positive, is small and imprecisely estimated. This suggests that, at least over the 2005–2024 period and in the absence of a binding DPP requirement, technological maturity has not historically been a strong driver of which countries gain or lose EU textile market share. Nonetheless, the FTR is a very stable index, that has only been measured since 2010. Therefore, the same tests were performed using the World Bank's internet connection index (per 100 people), which can be found in Appendix 2. However, this index is very broad and had a non-significant relationship with market share at the 5% level across all tests. Regulatory quality and supply chain concentration (HHI) tell a more layered story: both show sign reversals between the linear fixed-effects model and the GEE fractional logit model, but the Mundlak decomposition clarifies the apparent contradiction as a robustness check. For HHI, the within-country effect is positive, precisely estimated, and the strongest coefficient observed in the entire econometric analysis (β = 0.0085, p = 0.001). This indicates that as a given exporter's supply base becomes more concentrated over time, its EU market share tends to rise. This could for instance suggest that the cost efficiencies, volume scale, and streamlined logistics achieved through a concentrated supply network outweigh the risk-mitigation benefits of a fragmented, diversified sourcing strategy, at least at a firm level (Molinaro et al., 2022). For regulatory quality, the within-country effect is positive but insignificant, while the between-country effect is negative and marginally significant, suggesting that countries with persistently high regulatory quality are not, on average, the dominant exporters in this market. This is plausibly because they are often not the lowest-cost producers, as can be seen from the cluster analysis.

This divergence between within-country and between-country effects is, in itself, a substantive finding. It indicates that historical EU market share has been shaped more by the structural characteristics that distinguish countries from one another (their concentration profile, broadly defined regulatory environment, and economic scale) than by the kind of marginal improvements in digital or regulatory capacity that the DPP is meant to incentivise going forward. In other words, the historical record provides only limited evidence that readiness, as currently measured, has been a strong determinant of competitiveness in the pre-DPP era. This is consistent with the broader literature's observation that DPP-specific costs and capabilities have not yet been priced into trade relationships (Acciai & Pérez-Bou, 2025; Domskienė & Gaidule, 2024), precisely because the DPP has not yet entered into force. The weak explanatory power of FTR and RQ should therefore not be read as evidence that readiness will be irrelevant once the regulation is binding, but rather as a baseline against which the regulation's future effects can be measured.

It is the exposure-readiness matrix (H3) that translates these findings into forward-looking, policy-relevant terms. By combining historical EU market dependence with the composite readiness score derived from the cluster analysis, the matrix identifies Bangladesh, Turkiye, and Pakistan as occupying the highest-risk position: substantial reliance on the EU market combined with comparatively weak structural readiness. This finding is especially significant for Bangladesh, whose EU market share nearly tripled between 2005 and 2023 and which is simultaneously placed in the lowest readiness tier in the cluster analysis. China presents a contrasting case: despite holding by far the largest EU market share, its moderately positive readiness score places it closer to a position of "resilient dominance" rather than acute exposure, suggesting that scale and accumulated technological capacity may partially offset readiness gaps that would otherwise be more concerning. High-income exporters with minimal EU textile dependence (Switzerland, the Republic of Korea, Japan, the United Kingdom, and the United States) occupy the opposite corner of the matrix: high readiness but low exposure, meaning the DPP is unlikely to materially affect their position in this market regardless of how stringent its requirements become. However, they still have the issue of re-exporting, where they will need the data of the products they import and then re-export to the EU (Wang et al., 2010). The exposure-readiness matrix identifies a clear cohort (Bangladesh, Türkiye, Pakistan, and to a lesser extent India, Morocco, Tunisia, Sri Lanka) combining high EU market reliance with low composite readiness. Because the DPP is not yet in force, this confirms the existence and identity of the structurally vulnerable cohort that remains a classification-based inference rather than a tested outcome.

5.2 Theoretical implications

These results extend the literature on DPPs in several ways. First, by empirically operationalising "readiness" through quantifiable technological, regulatory, and structural indicators, this thesis moves the DPP readiness debate beyond the qualitative, framework-based approaches (SWOT, Porter's Cluster Theory) that Colasante et al. (2025) and Fares et al. (2025) identify as dominant in the field. The three-cluster typology offers a replicable and updatable classification that future research can apply as the DPP's technical specifications, and the underlying trade data, evolve. This cluster analysis also supports the largely qualitative claims found in the United Nations Industrial Development Organization (2025) assessment of Bangladesh, India, and Egypt. It but does so on a systematic country level with a larger sample of 20 of the EU's major textile-exporting partners.

Second, the findings speak directly to the "supply chain divergence" thesis advanced by Bastos Lima and Schilling-Vacaflor (2024) in the context of EU due diligence regulation in Brazilian soy supply chains. The weak historical relationship between readiness indicators and EU market share suggests that, to date, exporters have not needed to differentiate EU-bound production from production destined for other markets on the basis of regulatory or technological capacity. There has been no DPP-specific cost to avoid. Whether this changes once the DPP becomes binding is an open empirical question that this thesis cannot resolve directly (since the regulation is not yet in force), but the exposure-readiness matrix offers a theoretically grounded basis for predicting where such divergence is most likely to emerge. In countries combining high EU dependence with low readiness, such as Bangladesh and Pakistan, the economic incentive to maintain separate, lower-cost supply chains for non-EU markets while concentrating compliance efforts on EU-bound goods would be strongest.

Conversely, for low-readiness, low-exposure countries, divergence is less likely simply because the EU market share at stake is too small to justify dedicated investment either way.

Third, the within/between divergence identified in the Mundlak specifications contributes a methodological insight to the broader literature on regulatory readiness and trade competitiveness. Across the readiness indicators, the within-country coefficients, capturing whether a given exporter's own improvement in readiness over time translates into market share gains, were consistently small and, with the exception of HHI, statistically insignificant. The more informative and consistent signal instead came from the between-country dimension: it is the structural differences that distinguish one exporter from another (for instance, their persistent average level of regulatory quality), rather than how much a given country's indicators changed from year to year, that appear to account for variation in EU market share. This suggests that EU textile market share is shaped primarily by relatively fixed, structural characteristics of an exporting economy rather than by short-term or marginal gains in readiness.

This distinction matters theoretically because readiness, as captured by these indicators, appears to be a relatively stable, slow-moving characteristic of each exporting economy rather than something that changes markedly from year to year. It is the gap between countries, not the pace of change within a given country, that is associated with differences in market position. This raises an interesting question for the period after the DPP enters into force: whether this same between-country pattern will persist, with readiness remaining a largely static marker that distinguishes exporters from one another without itself driving change, or whether the introduction of binding DPP requirements will activate readiness as a dynamic factor, such that exporters who manage to improve their readiness over time begin to see this translate into shifts in market share. The historical evidence presented here cannot answer this question directly, since it predates the regulation, but it does establish the relevant baseline against which any such shift could be assessed.

Finally, by demonstrating that supply chain concentration (HHI) is the single most robust within-country predictor of EU market share, these results provide optimism that the upcoming Digital Product Passport (DPP) mandate will not severely distort existing trade dynamics. Because the DPP framework fundamentally relies on traceable, consolidated supply chains to support its track-and-trace data infrastructure, highly concentrated networks are naturally more compatible with its stringent compliance requirements (Langley et al., 2023). However, this idea that concentration is better (in the case of the DPP) must be weighed against a changing global reality. Since COVID-19 and the recent weaponization of trade, many buyers are aggressively diversifying their supply chains to prioritize resilience over pure cost-efficiency (Farrell & Newman, 2019; Fernandez-Stark et al., 2022). This structural shift towards de-risking heavily explains why highly concentrated exporters, most notably China, have seen a decline in their EU market share . This nuance has not, to the author's knowledge, been articulated in the existing DPP literature and represents a contribution of this thesis to the theoretical understanding of how structural trade characteristics and regulatory requirements can pull in different directions.

5.3 Policy implications

The findings carry several implications for EU policymakers, the European Commission's Joint Research Centre as it finalises the textile-specific delegated acts under the ESPR, and for the exporting countries themselves. For EU policymakers, the exposure-readiness matrix offers a concrete prioritisation tool. Rather than applying a uniform technical-assistance strategy across all extra-EU textile exporters, the results suggest that transitional support, capacity-building programmes, and phased compliance deadlines could be targeted first at the high-exposure, low-readiness countries identified in this thesis, most notably Bangladesh, Turkiye, and Pakistan. Given that Bangladesh alone accounted for close to a fifth of EU textile imports by 2023 while ranking among the least prepared exporters in the sample, a disorderly transition in this single supply relationship could have disproportionate effects on both EU import availability and Bangladeshi export revenues. This is consistent with calls in the literature for tailored, country-specific strategies rather than one-size-fits-all approaches (Carvalho et al., 2025). This finding should be taken into account into the upcoming impact assessment that is currently being conducted by the Joint Research Centre (European Commission & Joint Research Centre, 2025a).

For the Commission, the result that supply chain concentration, not technological or regulatory readiness, is the strongest historical predictor of market share retention (H2) is a signal that compliance costs are likely to fall most heavily on exporters whose supply chains are concentrated but under-resourced technologically. These countries currently rely on the very structural feature, concentration, that has historically supported their market position, without necessarily possessing the regulatory or digital capacity the DPP requires. Designing graduated compliance pathways, recognising this combination of conditions, could reduce the risk of abrupt EU market exit for the most exposed exporters while preserving the DPP's underlying transparency objectives.

For exporting-country governments and industry associations, particularly in Bangladesh, Pakistan, and Turkiye, the results point to two complementary priorities: strengthening regulatory enforcement capacity (where the within-country effect, though not significant, was directionally positive) and, more urgently, addressing supply chain concentration in ways that are compatible with traceability requirements rather than simply diversifying away from them. Because concentrated supply chains were found to support EU market share historically, a wholesale diversification strategy pursued purely to reduce HHI could be counterproductive. The more promising policy direction is to use the existing concentration as a foundation for traceability infrastructure (since fewer, larger supply relationships are, in principle, easier to digitise and standardise) rather than treating concentration and DPP-readiness as opposing goals. Nonetheless, this is easier said then done in a an era of supply-chain weaponization and diversification (Farrell & Newman, 2019; Fernandez-Stark et al., 2022).

Finally, for SMEs and intermediary supply chain actors across all three readiness clusters, the findings reinforce the literature's concern that compliance costs could disproportionately burden smaller firms and reinforce market concentration in favour of larger, vertically integrated companies (Carvalho et al., 2025). Given that Group 3 countries combine the lowest readiness scores with the most SME-dominated textile sectors (United Nations Industrial Development Organization, 2025), targeted financial and technical assistance mechanisms, potentially channelled through EU trade and development cooperation instruments, would help ensure that the DPP works without excluding the exporters most central to the EU's textile supply chain.

6. Conclusion

This thesis set out to answer the research question: how ready are textile-exporting countries to adopt the Digital Product Passport, and how can this readiness be assessed and quantified? In response to the absence of systematic, quantitative assessments of DPP readiness identified in the literature (Carvalho et al., 2025; Karabulut et al., 2025), this thesis developed and applied a three-part methodology combining cluster analysis, panel-data econometrics, and an exposure-readiness matrix to the EU's major textile-exporting partners.

The significance of this thesis is threefold. Empirically, it provides the first systematic, quantified readiness assessment covering 20 of the EU's major textile-exporting partners, addressing a gap that previous studies, constrained by small samples or qualitative methods (Carvalho et al., 2025; United Nations Industrial Development Organization, 2025), were unable to fill. Theoretically, it related to the "supply chain divergence" idea (Bastos Lima & Schilling-Vacaflor, 2024) by interpreting the results as such that the risk of fragmented rather than broad-based transformation depends on the interaction between a country's structural readiness and its dependence on the EU market. It also reveals a previously unarticulated tension: while supply chain concentration historically drove market share and now facilitates DPP readiness, it simultaneously exposes exporters to higher risks from trade weaponization and supply shocks. (Farrell & Newman, 2019; Fernandez-Stark et al., 2022). Practically, the cluster analysis and exposure-readiness matrix offer EU policymakers and exporting-country stakeholders a concrete, replicable tool for prioritising technical assistance and phased compliance strategies, identifying Bangladesh, Turkiye, and Pakistan as the exporters facing the greatest structural risk under the upcoming regulation.

6.1 Limitations

Several limitations should be acknowledged. First, because the DPP is not yet in force, the second and third research question could not be tested econometrically. The exposure-readiness matrix is necessarily a structural, descriptive tool rather than a causally validated predictor of post-DPP outcomes, and its conclusions should be read as risk indicators rather than forecasts. Second, the readiness indices rely on proxies, the Frontier Technology Readiness Index and the World Bank Regulatory Quality indicator, that capture broad national capacity rather than textile-sector-specific digital or regulatory infrastructure; a country's overall ICT maturity or governance quality may not fully reflect the capabilities of its textile industry specifically. Third, the HHI calculations for several exporters relied on proxy data (exports reported by partner countries) where direct import data were unavailable, introducing a likely upward bias in measured concentration for the affected countries. Fourth, the panel analysis covers the period 2005–2024, entirely prior to the DPP's entry into force, meaning the econometric results describe the drivers of historical market share rather than the regulation's anticipated effects. The consistently weak significance of the readiness variables should be interpreted in this light rather than as evidence that readiness will remain irrelevant once compliance becomes mandatory. Moreover, the low R-squared values suggest potential omitted variable bias. Limiting the model to just three composite indicators and GDP likely overlooks several other key variables that actively drive market share.

6.2 Directions for future research

Building on these limitations, several avenues for future research emerge. As the ESPR's textile-specific delegated acts and DPP technical specifications are finalised and the regulation enters into force, longitudinal research tracking actual changes in EU market share, trade patterns, and compliance behaviour following implementation would allow the exposure-readiness matrix developed here to be empirically validated. This would permit a direct test of the supply chain divergence hypothesis (Bastos Lima & Schilling-Vacaflor, 2024) that the present, pre-implementation data cannot support. Future studies could also develop sector-specific readiness indicators, for instance measures of textile-specific digital infrastructure, traceability technology adoption, or sector-level regulatory enforcement, to complement the broad national-level proxies used in this thesis. Finally, qualitative or mixed-methods research engaging directly with firms, particularly SMEs in the Group 3 "emerging/developing" cluster identified in this thesis, would help to explain the firm-level mechanisms underlying the structural patterns identified here, and to test whether the policy recommendations proposed in this thesis, in particular leveraging existing supply chain concentration as a foundation for traceability infrastructure, are viable at the level of individual exporters.

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Appendix 1

The *Calinski–Harabasz* pseudo-F statistic is used in the cluster analysis to provide an objective, statistical measure of how well different clustering solutions perform. It compares the variation between clusters to the variation within clusters, helping to assess whether groups are clearly separated or still too similar. This is important because visual inspection of dendrograms or cluster plots can be subjective and may not always reliably identify the optimal number of clusters. By applying this criterion, the analysis ensures a more robust and data-driven selection of the appropriate cluster solution, balancing internal similarity within clusters with clear separation between them. In the formula, the "between-cluster" variation (Trace(B)) measures how far apart the clusters are from each other, while the "within-cluster" variation (Trace(W)) measures how close the observations are within each cluster. These are then adjusted by the number of clusters (k) and the total number of observations (n). A higher value of the statistic indicates better-defined clusters, meaning that the groups are more distinct and internally more similar.

$$\text{Calinski} - \text{Harabasz pseudo} - F = \frac{Trace(B) \big/ (k-1)}{Trace(W) \big/ (n-k)}$$

The results for the raw HHI and log HHI are as follows:

Table:

Calinski-Harabasz stopping criteria raw HHI

Clusters (k)	Pseudo-F Statistic
2	17.40
3	25.31
4	33.57
5	31.84

Source: Author's calculation using Stata. Data: UN Comtrade, UNCTAD and World Bank.

Table:

Calinski-Harabasz stopping criteria log HHI

Clusters (k)	Pseudo-F Statistic
2	19.27
3	19.61
4	19.53
5	19.39

Source: Author's calculation using Stata. Data: UN Comtrade, UNCTAD and World Bank.

Four groups are optimal for the raw HHI, three groups are optimal for the log HHI. Following tables give an overview of the characteristics of the clusters. Since clustering is based on standardized variables, cluster characteristics are interpreted in relative terms (i.e., above or below the sample mean), ensuring consistency with the underlying distance measures used in the analysis.

Table:
Cluster groups overview raw HHI

Cluster Group (group4)	RQ (Mean)	FTR (Mean)	HHI (Mean)
1	1,495	1,295	-0,538
2	-0,147	0,278	-0,452
3	-0,613	-0,821	0,239
4	-1,693	-1,573	3,487

Source: Author's calculation using Stata. Data: UN Comtrade, UNCTAD and World Bank.

Table:
Cluster groups overview log HHI

Cluster Group (group3)	RQ (Mean)	FTR (Mean)	Log(HHI)(Mean)
1	1,495	1,295	-0,621
2	-0,147	0,278	-0,484
3	-0,733	-0,905	0,668

Source: Author's calculation using Stata. Data: UN Comtrade, UNCTAD and World Bank.

Appendix 2

Table: Two-Way Fixed Effects

VARIABLES	(1) Marketshare
Internet Connection	-0.000352*
	(0.000211)
RQ	0.00305*
	(0.00156)
HHI	0.00691*
	(0.00412)
GDP	-0
	(0)
Observations	1,162
Number of Countries	83
R-squared	0.288

Note: *Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculation using Stata*

Table: Fractional Logit (GEE)

VARIABLES	(1) Marketshare
Internet Connection	-0.0183
	(0.0188)
RQ	-0.864**
	(0.353)
HHI	-9.539*
	(5.197)
GDP	0***
	(0)
Observations	1,162
Number of Countries	83

Note: *Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculation using Stata.*

Table: Mundlak (CRE)

VARIABLES	(1) Marketshare
Internet Connection	-0.000348*
	(0.000205)
RQ	0.00304*
	(0.00155)
HHI	0.00691*
	(0.00412)
GDP	-0
	(0)
mean_FTR	-0.0103*
	(0.00528)
mean_RQ	-0.0671**
	(0.0293)
mean_HHI	0
	(0)
mean_GDP	-0.000348*
	(0.000205)
Observations	1,162
Number of Countries	83

Note: *Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculation using Stata.*