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The changing topology of global textile exports: A network perspective

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Abstract

This paper investigates the changing topology of the global textile export network from 1990 to 2020, using network analysis methods. By examining major centrality measures, including total degree, closeness, betweenness, eigenvector centrality, density, and clustering coefficient, we measure the structural evolution and strategic positions of countries within this trade network over time. Our analysis reveals significant transformations in the network's topology, highlighting the growing disconnectedness and interdependence between nations. The leading countries in the network are Germany, the USA, the UK, India, and China. However, due to the pandemic in 2020, there was a contraction in the inter connectivity and interdependence between countries. Although network density slightly decreased in 2020, the overall trend points to increasing integration and efficiency of information transfer, denoting a resilient and cohesive global trade structure. The study's findings emphasize the need for strengthening competitiveness and strategic planning to manage future shocks and disruptions. Overall, mapping changes in the configurations of the textile export network using centrality metrics provides valuable insights into the dynamic nature of global trade inter linkages.

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1. Introduction

Transformations in the global trade landscape over recent decades have reshaped the international economic order, impacting economies worldwide. The expansion of world trade has led to a significant increase in the volume and value of goods and services crossing borders. This growth can be partly attributed to the reduction or elimination of tariffs and trade barriers in many countries, facilitating smoother international business transactions. As a result, the textile and manufacturing industries have shifted across different countries seeking low-cost manufacturing bases, creating complex trade networks (Wei et al., 2012). Countries like Bangladesh, Turkey, and Cambodia have successfully leveraged duty-free access to major markets like the European Union and the United States, gaining a competitive advantage.

Examining a country's role in the global textile trade through conventional metrics such as export share, production capacity, import volume, and its position in the global supply chain provides a limited understanding. Network analysis offers a more comprehensive approach by considering global trade as an intricate system where countries are involved in export and import activities, interdependent at both individual and aggregate levels. Unlike traditional openness metrics (e.g., trade-to-GDP ratio), network analysis captures the nuanced nature of how countries connect through exports and imports. This approach provides a more comprehensive exploration of international economic integration by considering the connectivity dimensions between trading countries (Cepeda-López et al., 2019).

Analysing network metrics dynamically provides insights into structural changes over time. It also helps in understanding the importance of specific nodes (countries) through centrality measures (Yu et al., 2020). Against this backdrop, the current study aims to explore the trade structure, position, and interconnectedness in the global textile export network. The available literature shows that the application of network analysis to international trade as a tool has been evident in seminal works (Wallerstein, 1987; Snyder and Kick, 1979). For instance, network analysis has been applied to comprehend the world trade network (De Benedicts et al., 2014; Vidya et al., 2020) and global value chains (Sui et al., 2021). Recent literature has extended this approach to specific commodities, such as oil (Zhong et al., 2014), metals (Hu et al., 2019), and automotive components (Amighini and Gorgoni, 2014). Notably, recent research has delved into the impact of COVID-19 on the world trade network (Vidya et al., 2023; Kiyoto, 2022; Vidya and Prabheesh, 2020). Given this, existing studies have not captured the textile sector as a single entity. This study attempts to fill this gap by conducting a detailed analysis over a long-time span from 1990 to 2020.

To achieve this, the study addresses the following research questions: (i) What is the structure and position of countries in the global textile export network? (ii) Which countries are the leading participants in the textile trade network? (iii) What is the trade intensity, clustering tendency, and closeness among countries in the network?

This study employs a trade network analysis approach focused on the top fifty textile exporting nations. The sample countries are selected based on their cumulative export value to the world from 1990 to 2021. The analysis examines the network structure across seven specific years i.e., 1990, 1995, 2000, 2005, 2010, 2015, and 2021. This year’s chosen to represent different periods and policy shifts impacting the global textile trade. By calculating network centrality measures including degree, closeness, eigenvector, betweenness, and density, the study uncovers the evolving topology of the global textile export network over three decades. This approach reveals the key countries emerging as central nodes through their connectivity patterns and provides insights into the strategic positioning of nations within this intricate trade system.

The findings highlight the complex and dynamic nature of the global textile export network, reflecting broader economic and policy shifts. The network has become more interconnected and influential over time, with specific countries playing pivotal roles. This study contributes to the literature in several ways. Firstly, it offers a comprehensive analysis of the evolution of the global textile export network over three decades, providing insights into the changing dynamics of global trade patterns. Secondly, by employing network analysis, this study uncovers the nuanced shifts in trade relationships that traditional metrics might overlook. The paper also contributes to the literature by highlighting the importance of network centrality measures in understanding the strategic positions of countries within the global trade network.

2. Data and Methodology

The paper used textile sector trade data published by ITC and World integrated trade solutions (WITS). To represent the trade network, we compared the structure of the textile trade network for seven periods i.e., 1990,1995,2000,2005, 2010, 2015 and 2020.We address the research issue from the top 50 global textile exporting countries based on their export contribution to global trade. The list of sample countries is Australia, Austria, Bangladesh, Belgium, Brazil, Bulgaria, Cambodia, Canada, China, Colombia, Czechia, Denmark, Egypt, El Salvador, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Italy, Japan, South Korea, Lithuania, Macao, Malaysia, Mexico, Morocco, Netherlands, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Romania, Singapore, Slovakia, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Aarab Emirates(UAE), United Kingdom(UK),United States of America (USA), and Vietnam.

Network analysis represents countries and their relationships in the form of nodes and edges. Nodes represent individual countries, while edges represent the connections or relationships between these countries. The direction of edges corresponds to the direction of the textile trade. The first step involved calculating the cumulative value of textile exports for each country from 1990 to 2020. Subsequently, the top fifty countries were selected based on their export values. The network relations between these fifty sample countries were then examined using Gephi 0.9.2, a network analysis application. To simplify the network graph and enhance visibility, the focus was primarily on the top fifty countries. In the network graph, partner countries were represented as edges without explicitly labelled nodes. This filtering process aimed to highlight the most significant trade relationships within the network, providing a clearer understanding of the overall dynamics of textile exports. Based on the criteria, the network was constructed for the years 1990, 1995, 2000, 2005, 2010, 2015, and 2020. The top fifty exporters were represented as nodes in the global textile export trade network map, while the links or edges between nodes depicted the trade flows of textile exports. The countries are presented as nodes in a global textile export trade network map, and their export trade flows are shown as links.

The export value from country i to j indicates by W_{ij};

$Export_{it} = \sum_{j=1}^{N-1} W_{ij}$ “ (1)”

Where $Export_{it}$ countries export value for the country i, at time t, respectively. The relative importance of each node is represented by the centrality measures.

Table 1. Terms and Descriptions used in Network Analysis.
This table provides definitions and explanations for key terms used in network analysis.

Term	Description
Centrality	It shows a how a node is positioned in a network and how important it is.
Degree	It is the count of all connections linked to a vertex, encompassing both incoming and outgoing links.
Closeness Centrality	It represents the how close one node (in terms of topological distance) is with respect to all other nodes. The smallest path connecting country i and country j is denoted by the geodesic distance between i and j.
Eigenvector Centrality	It shows the how important a node is to the nodes around it; countries that carry a high value of eigenvector centrality are the ones that are connected to many other countries which are, in turn, connected to many others.
Betweenness Centrality	The betweenness centrality for each vertex is the number of shortest paths that pass through the vertex.
Clustering Coefficient	The clustering coefficient is defined as the ratio of number of edges between the neighbors of node and maximum number of edges that could exist between the neighbor of node. This can be calculated as averaged over all nodes.

Source: Vidya et al. (2020).

The detailed definitions of each centrality measures are presented in the Table 1. We use network centrality parameters such as degree, closeness, eigenvector, betweenness, clustering coefficient and density to examine the structural changes in the global textile trade and positioning India.

3. Results and Discussion

The structural changes in the global textile export network and the average value of each metric in network analysis are presented in Table 2.

Table 2. The Network Metrics
This table presents the metrics analysed for the global textile export network from 1990 to 2020. The metrics include Density, Betweenness Centrality, Closeness Centrality, Eigenvector Centrality, and Clustering Coefficient.

Metrics	1990	1995	2000	2005	2010	2015	2020
Density	0.067	0.116	0.131	0.142	0.144	0.147	0.139
Betweenness Centrality	0.000879	0.00158	0.00170	0.00158	0.00155	0.00140	0.00136
Closeness Centrality	0.327	0.626	0.719	0.753	0.759	0.769	0.737
Eigen vector Centrality	0.883	0.898	0.908	0.946	0.939	0.953	0.941
Clustering Coefficient	0.327	0.626	0.719	0.753	0.759	0.769	0.737

Source: Author’s own calculation.

Network density measures the ratio between the actual number of connected edges among nodes in a complex social network and the maximum number of possible connections (Lancichinetti et al., 2010). It indicates the degree of interconnectedness among the nodes within the network. A higher network density suggests a denser network with stronger links between nodes and more intimate relationships. Conversely, a lower network density implies weaker connections and less intimacy among the nodes. The results from Table 2 reveal that the global textile export network has been expanding over time, as the actual links between countries have increased. In 1990, the network density was only 0.067, and it grew to 0.116 in 1995, 0.131 in 2000, 0.142 in 2005, 0.144 in 2010, and 0.147 in 2015. However, in 2020, the network density decreased to 0.139.

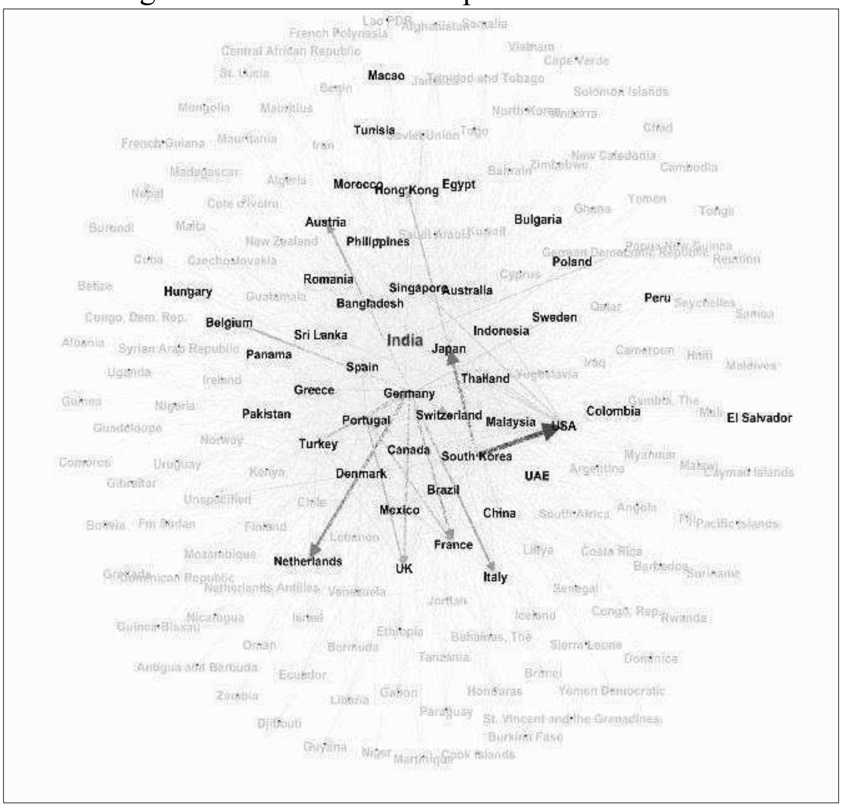
Similarly, betweenness centrality measures the extent to which a node falls on the shortest path between other nodes in the network (Wang et al., 2008). Countries with high betweenness centrality act as commercial bridges with other countries in the trade network. The betweenness centrality value increased from 0.000879 in 1990 to 0.00136. This indicates a rise in the importance of countries as intermediaries in the global trade network. The highest recorded value was observed in 2000 with a betweenness centrality of 0.00170. From 2000 to 2020, the values show a slight difference, suggesting a stable level of betweenness centrality during that period.

The closeness centrality is a metric that indicates how close a node is to the center of the network. The higher the value, the more central the node is to the network, and the shorter the distance between the node and the other nodes, the faster the speed of information transfer (Zhang et al., 2020). Table 2 displays the average closeness centrality values in the global textile export network for different years. In 1990, the average closeness centrality was 0.327, indicating a relatively lower level of centrality and closeness among the countries involved in the textile trade. However, the values increased over time, reaching 0.626 in 1995, 0.719 in 2000, 0.753 in 2005, and 0.759 in 2010. The highest recorded value was observed in 2015 with a closeness centrality of 0.769. However, in 2020, the average closeness centrality decreased slightly to 0.737. The increasing closeness centrality of the textile export network carries several implications. Firstly, it indicates that countries in the network are growing more interdependent. This implies that changes in one country's textile trade can have a knock-on effect on other countries in the network. Secondly, the rising closeness centrality facilitates easier information flow between countries in the network. This, in turn, can lead to faster innovation and economic growth.

Eigenvector centrality measures the node's influence based on its neighbors. A node possesses high eigenvector centrality if it is connected to many other nodes of high centrality (Zhao et al., 2020). In the context of a trade network, eigenvector centrality can be used to identify nodes (countries) that have a high influence or importance within the network. It considers not only direct connections but also the centrality of its neighbouring nodes. In other words, it assesses both the quantity and quality of connections. In 1990, the average eigenvector centrality value in the global textile export network was 0.883. This value indicates the overall influence of countries within the network at that time. Over the years, the average eigenvector centrality values increased, suggesting a growing influence of sample countries in the global textile trade. The values rose to 0.898 in 1995, 0.908 in 2000, 0.946 in 2005, and 0.939 in 2010. The highest recorded value of 0.953 was observed in 2015, indicating a significant increase in the average eigenvector centrality and thus the influence of countries in the textile export network. However, in 2020, the average eigenvector centrality slightly decreased to 0.941. This decrease may indicate a slight decline in the overall influence of countries within the network. Despite this decline, it is important to note that the centrality values are still relatively high compared to the initial value in 1990. Therefore, even with a slight decrease, the countries in the textile export network continue to exhibit a significant level of influence and importance in the global textile trade.

The clustering coefficient represents the degree of connectivity that a node has with its neighbors. High values of clustering coefficients indicate close trade relationships between countries in the trade networks. The clustering coefficient measures the tendency for nodes in a graph to cluster together. High clustering coefficients show that nodes tend to form tightly knit groups characterized by a high density of ties (Clemente et al., 2018). The average clustering coefficient value in the global textile export trade network was 0.327. This high value suggests that the countries involved in the textile trade had a strong tendency to form close trade relationships and cluster together within the network. The high density of connections indicates a significant level of cohesion within the trade network. The average clustering coefficient values showed an increasing trend over the years. By 1995, the value increased to 0.626, indicating a slight increase in the density of connections and the tendency of nodes to cluster together. The clustering coefficient further increased to 0.719 in 2000. From 2005 to 2020, the clustering coefficient values remained stable with minor fluctuations. In 2005, the value was 0.753, in 2010 it was 0.759, and in 2020 it was 0.737. The highest average clustering coefficient value was observed in 2010 at 0.759, suggesting the presence of strong tight-knit groups within the trade network. These values indicate that the level of clustering and the density of connections among countries in the textile export trade network did not change significantly during this time. The increasing trend in the average clustering coefficient values suggests a slight increase in the tendency of nodes to form tightly knit groups or clusters within the global textile export trade network.

Figure 1. Global Textile Export Network – 1990

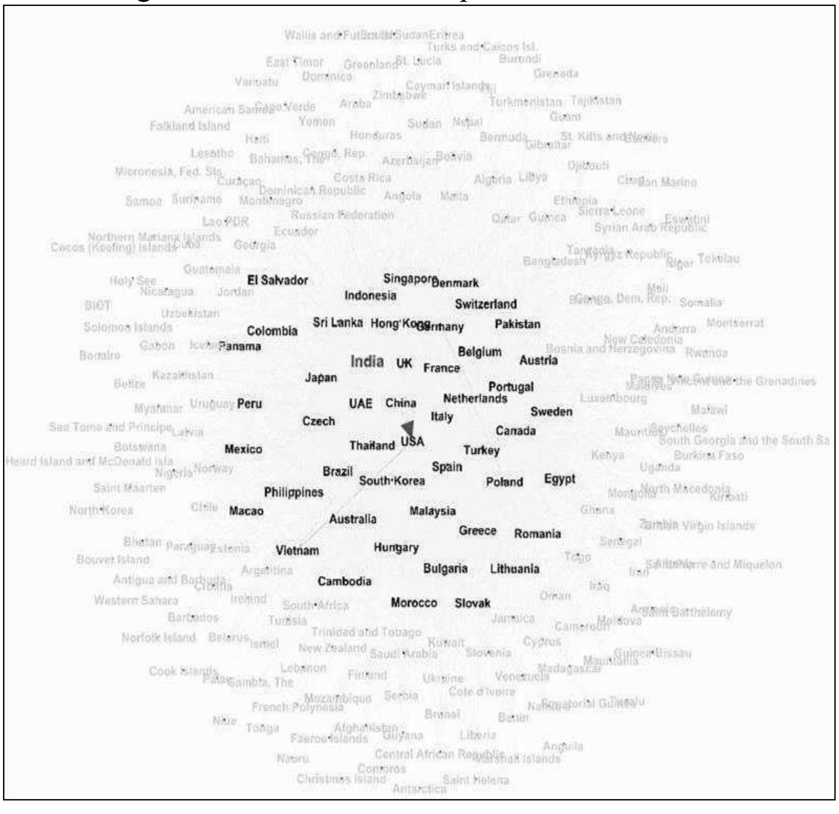


Source: Author's representation using network analysis.

Figure 1 represents the global textile export network for the year 1990. The sample countries are represented by black labels, and their export partners are depicted in transparent black color, with the lines between them representing the amount of textile trade. The thicker black lines indicate the highest levels of trade. In 1990, the highest levels of textile trade were observed between South Korea, Japan, the United States, Germany, France, Italy, and the Netherlands, marking these countries as major exporters in global textile exports that year. In terms of total degree (the number of connections a country has with other countries), Germany had the most connections, followed by Japan and India. These countries also had the highest closeness centrality values, measuring how close a country is to all other countries in the network.

In terms of betweenness centrality, which measures how often a country lies on the shortest path between two other countries, Germany, Japan, and Australia had the highest values, indicating their roles as important intermediaries in the network. Regarding eigenvector centrality, which assesses a country's importance in the network based on the importance of its neighbors, Austria, Belgium, and China had the highest values, making them the most influential in the global textile export network. In summary, Germany emerges as a significant player in terms of total degree, closeness centrality, and betweenness centrality, with Japan also ranking high in these measures. India occupies the third place in terms of total degree and closeness centrality.

Figure 2. Global Textile Export Network – 2020



Source: Author's representation using network analysis.

Figure 2 shows the global textile export network of selected countries in 2020. The sample countries are represented by black labels, and their export partners are depicted in transparent black color, with the lines between them representing the amount of textile trade. The thicker green lines indicate the highest levels of trade. In 2020, the highest levels of textile trade were between China, the United States, and Vietnam. In terms of total degree (the number of connections a country has with other countries), China had the most connections, followed by the UK and the USA. These countries also had the highest closeness centrality values, measuring how close a country is to all other countries in the network.

In terms of betweenness centrality, which measures how often a country lies on the shortest path between two other countries, the UK, USA, and China had the highest values, indicating their roles as important intermediaries in the network. Regarding eigenvector centrality, which assesses a country's importance in the network based on the importance of its neighbors, Bangladesh, the UK, and France had the highest values. These countries were the most influential in the global textile export network.

Table 3. Centrality Rankings of Top 10 Textile Exporting Countries for Selected Years (excerpt of top 10 nodes).

The table shows the top 10 textile exporting countries based on these centrality measures for selected years, illustrating how the importance and influence of different countries within the network have changed over time.

Year	Total Degree	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
1990	Germany, Japan, India, Switzerland, Thailand, Spain, South Korea, Canada, Portugal, Denmark.	Germany, Japan, India, Switzerland, Thailand, Spain, South Korea, Canada, Portugal, Denmark	Germany, Japan, Australia, India, Switzerland, Spain, Thailand, Canada, South Korea, Denmark.	Austria, Belgium, China, France, Italy, Netherlands, Pakistan, Philippines, Sweden UAE.
1995	UK, Germany, USA, Italy, Netherlands, Belgium. France, Thailand, China, India.	UK, Germany, Thailand, USA, Italy, China, Netherlands, Belgium, France, India.	UK, USA, Germany, India, France, Australia, Japan, Netherlands, Italy, Belgium	Austria, France, UK, USA, Canada, Spain, Germany, Belgium, Italy, Netherlands
2000	UK, Germany, Indonesia, USA, Italy, China, Thailand, India, France, Belgium.	Indonesia, UK, Germany, Thailand, USA, Italy, China, India, Belgium, France.	USA, Indonesia, UK, Italy, Germany, South Korea, India, Netherlands, France, China	France, UK, USA, Spain, Italy, Denmark, Greece, Austria, Canada, Germany
2005	Germany, India, the UK, USA, China, Pakistan, Italy, Thailand, Netherlands, France.	Germany, India, the UK, USA, China, Pakistan, Thailand, Italy, Netherlands, France.	Germany, USA, UK, Pakistan, India, Indonesia, France, Thailand, Netherlands, China.	France, UK, USA, Mexico, Colombia, Panama, Spain, Italy, Denmark, Greece
2010	China, India, Germany, UK, USA, France, Thailand, Netherlands, Italy, Indonesia.	China, India, Germany, UK, USA, France, Thailand, Netherlands, Italy, Indonesia	USA, India, UK, Indonesia, Australia, China, Thailand, Germany, Italy, France.	France, UK, USA, Mexico, Spain, Italy, Denmark, Greece, Canada, Germany
2015	Germany, UK, China, USA, France, India, Italy, Netherlands, Thailand, Spain	Germany, UK, China, USA, France, India, Netherlands, Thailand, Italy, Spain.	USA, Germany, China, UK, France, Australia, Spain, Italy, India, Austria.	France, UK, USA, Spain, Italy, Canada, Belgium, China, Brazil, Singapore, Vietnam.
2020	China, UK, USA, India, Italy, Germany, France, Netherlands, Belgium, Spain	China, UK, USA, India, Germany, Italy, France, Netherlands, Spain, Belgium.	UK, USA, China, Australia, France, Italy, India, Germany, South Korea, Belgium	Bangladesh, France, UK, USA, Italy, Canada, Belgium, Brazil, Mexico, UAE

Source: Author's own calculation.

Table 3 provides a detailed view of the shifts and trends in the global textile export network from 1990 to 2020, focusing on four key centrality measures: Total Degree, Closeness Centrality, Betweenness Centrality, and Eigenvector Centrality. These measures offer insights into the roles and influence of different countries within the network. Due to space constraints, the table shows only the top ten countries from the original selection.

The degree represents the number of direct connections (both imports and exports) each country has. Countries with higher rankings have more trade links, indicating significant roles in global textile trade. Germany, Japan, and India were prominent in 1990, showing their early importance. Over the years, the emergence of China, especially by 2010, and the consistent presence of countries like the UK, USA, India, and Germany highlight shifts towards these nations becoming central nodes in the textile trade network.

Closeness centrality represents how close a country is to all others in the network, suggesting efficiency in trade flow and the potential for influence over the network. The results from Table 3 highlight that in the context of closeness centrality, early dominance by European countries and Japan shifts towards a more diverse set of countries by 2020, including China, the UK, and the USA, illustrating changes in global trade dynamics and the rise of new textile powerhouses.

Betweenness centrality indicates a country's role as an intermediary in the trade network. High betweenness suggests a country's strategic position to control and facilitate trade flows between other countries. The USA's consistent appearance highlights its role as a key intermediary in global textile trade. The positions of countries in the network show diversity over time, with countries like Australia and South Korea appearing, indicating their strategic roles in connecting various parts of the network.

Eigenvector centrality measures a country's influence based on the centrality of its connections. It suggests that a country is influential not just because of the number of connections but also because it is connected to other influential countries. The presence of European countries like France and the UK across the years, alongside the emergence of Bangladesh and the UAE by 2020, points to the evolving influence within the textile trade network. Countries like Germany, the UK, the USA, India, and Italy demonstrate sustained significance in the network, maintaining top positions across various centrality measures over the years. From the results, we can observe the complexity and evolving nature of global trade networks, highlighting how countries' positions change over time due to economic growth, strategic trade relationships, and shifts in the global market landscape.

4. Conclusion

This paper undertakes a comprehensive analysis of the global network for textile export trade from 1990 to 2020, focusing on dynamics and structural change insights by applying a complex network analysis framework over three decades. In this manner, key centrality measures of a network, such as degree, closeness, betweenness, and eigenvector are applied to understand the evolving nature of global textile trade relationships and to test the significant changes in topology and deviation in average metric values in a manner like our study.

High interconnectedness and cohesion between countries were evidenced by the increased density and clustering between 2010 and 2020. Nevertheless, the downturn experienced in 2020 demonstrated that all countries globally remain vulnerable to global shocks, serving as a reminder of the potential deterrents to the development of global textile exports. Network density exhibited a clear upward trend, indicating an enhancement in the interconnectedness among nations within the textile trade network over time. Betweenness centrality, overall, increased from 2010 to 2020 and then stabilized, underscoring the growing importance of certain countries as bridges or intermediaries among others. Closeness centrality consistently rose throughout the period, signifying an escalating dependence among countries for accessing and moving goods through the textile trade network. Eigenvector centrality also displayed steady growth, suggesting that some nations gained more prominence over time due to their connections with other well-integrated networks. The clustering coefficient increased, highlighting the tendency for nodes to form tightly knit clusters and thus indicating strengthened localized cohesion within the network through the formation of dense sub-networks. However, in 2020, declines in network density, closeness centrality, and eigenvector centrality could be ascribed to external disruptions, such as supply chain interruptions from the COVID-19 pandemic, implying that this timeframe witnessed a contraction in the interconnectivity and interdependence between countries.

We also observed major changes in the global textile export trade network from 1990 to 2020, with respect to changing leadership and relationships among exporting countries. Initially represented by countries such as South Korea, Japan, Germany, and Italy, the scenario up to the year 2020 shifted towards emerging economies, with China, the USA, and Vietnam taking the lead. This shift reflected a significant transformation in global trade dynamics. Germany, the UK, the USA, India, and China stood as critical nations across most centrality measures throughout this period, underscoring their persistent relevance in the network. Eigenvector centrality transitioned from being dominated by European and North American countries to a more diversified group, including Bangladesh, Brazil, Mexico, and the UAE by 2020, signifying an increasing diversification and the rise of developing nations as influential nodes in the textile export network. This shift not only demonstrates the dynamic nature of global trade but also attests to the growing influence of emerging markets in shaping the future of the global textile industry.

The increasing interconnectedness of the global textile trade network points toward the need for innovation and improved competitiveness within the industry. Policymakers should create an environment favorable to research and development, the adoption of the latest technologies, and improvement in workforce skills to sustain a competitive position in the international market. The observed interdependence in the trade network clearly proves that any changes in the textile sector of a particular country will propagate through the network, hence necessitating strategic resilience planning. The COVID-19 pandemic's damaging consequences to the network's metric values in 2020 dramatically highlighted the susceptibility of such networks to disruptions and their potential to detract from global trade. Through strategic planning that includes resilience measures, policymakers can ensure trade continuity under all forms of diverse conditions in the textile trade. This strategy not only tackles immediate threats but also bolsters the textile industry to withstand future crises, thereby supporting global economic development.

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