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Resilient Supply Chain Networks Post-Pandemic: A Multi-Criteria Decision Analysis

OPEYEMI MORENIKE FILANI[1], JOHN OLUWASEUN OLAJIDE[2], GRACE OMOTUNDE OSHO[3]
[1]*Proburg Ltd, Lagos, Nigeria*
[2]*Unilever Nigeria PLC, Nigeria*
[3]*Guinness Nig. Plc, Nigeria*

Abstract- The COVID-19 pandemic exposed critical vulnerabilities in global supply chains, prompting the urgent need for resilient and adaptive supply chain network designs. This study presents a comprehensive framework utilizing Multi-Criteria Decision Analysis (MCDA) to evaluate and optimize post-pandemic supply chain resilience. By integrating qualitative and quantitative factors, the research identifies and prioritizes key resilience dimensions, including flexibility, redundancy, responsiveness, collaboration, and digitalization. A hybrid MCDA approach, combining Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), is employed to assess alternative supply chain configurations under uncertainty. The criteria are derived through expert consultation and literature synthesis, ensuring contextual relevance to post-pandemic disruptions such as labor shortages, transport constraints, geopolitical shifts, and demand volatility. Case application in the manufacturing sector demonstrates the practical relevance of the model. Results reveal that supply chains emphasizing local sourcing, agile distribution strategies, and digital integration outperform traditional cost-centric models in resilience rankings. Moreover, the incorporation of real-time data sharing and supplier diversification significantly enhances adaptability and recovery capabilities. The analysis provides strategic insights into trade-offs between efficiency and resilience, supporting decision-makers in reconfiguring supply chains to withstand future shocks. This research contributes to the growing body of knowledge on resilient supply chain design by offering a structured, data-driven method to navigate complexity and uncertainty in a post-pandemic world. It highlights the importance of adopting a holistic perspective that balances operational performance with long-term sustainability and risk mitigation. The proposed MCDA framework can serve as a decision-support tool for supply chain managers, policymakers, and stakeholders aiming to enhance systemic resilience without compromising competitiveness. Future research directions include integrating fuzzy logic for handling ambiguity and expanding the model to account for environmental and social sustainability metrics, ensuring alignment with broader sustainable development goals.

Indexed Terms- Resilient Supply Chain, Multi-Criteria Decision Analysis, Post-Pandemic Logistics, AHP, TOPSIS, Supply Chain Disruption, Risk Mitigation, Supply Network Design, Sustainability, Decision Support.

I. INTRODUCTION

The COVID-19 pandemic exposed profound vulnerabilities in global supply chain networks, disrupting production, transportation, and distribution systems across industries. From critical shortages of medical supplies and semiconductors to bottlenecks in food and consumer goods logistics, the pandemic underscored the fragility of globally interconnected supply chains that prioritize efficiency over adaptability (Akinluwade, et. al., 2015, Mustapha, et al., 2018). These disruptions highlighted the need for a strategic shift in supply chain design moving from lean and cost-focused models toward more resilient, responsive, and risk-aware structures capable of withstanding future shocks.

Supply chain resilience refers to the capacity of a supply network to anticipate, prepare for, respond to, and recover from unexpected disruptions while maintaining continuity of operations and minimizing performance degradation. It encompasses flexibility in sourcing and production, redundancy in critical components, collaboration among supply chain partners, and the agility to reconfigure logistics pathways. In a post-pandemic world marked by geopolitical uncertainty, demand volatility, and climate-related risks, building resilient supply chains is no longer a competitive advantage but a strategic necessity (Oni, et al., 2018).

Decision-making plays a pivotal role in enabling resilience. The ability to evaluate trade-offs between cost, speed, risk, and sustainability requires structured frameworks that incorporate both quantitative data and expert judgment. Multi-Criteria Decision Analysis (MCDA) provides a valuable approach to this challenge by allowing decision-makers to systematically assess multiple, often conflicting, criteria in identifying optimal supply chain strategies (Akpan, et al., 2017, Isa & Dem, 2014). Through the integration of techniques such as the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), organizations can prioritize resilience measures and select configurations that balance operational performance with risk mitigation.

This study aims to develop and apply an MCDA-based framework for evaluating resilient supply chain network alternatives in the post-pandemic context. The objectives are to identify key resilience dimensions, establish relevant decision criteria, and demonstrate the practical application of the framework using industry-relevant case scenarios. The paper is structured as follows: a review of relevant literature on supply chain resilience and MCDA techniques; a detailed explanation of the methodology and decision framework; presentation of results from a sector-based case study; discussion of implications and insights; and a concluding section outlining key contributions and future research directions (Abdalla & Esmail, 2019, Haleem & Javaid, 2019, Yakovleva, Sarkis & Sloan, 2012).

2.1. Literature Review

The concept of supply chain resilience has gained unprecedented attention in the aftermath of the COVID-19 pandemic, which exposed systemic vulnerabilities across global logistics and production systems. Supply chain resilience refers to a network's ability to prepare for unexpected disruptions, respond effectively, and recover swiftly while maintaining the flow of goods and services. Over the years, researchers have proposed a variety of frameworks to conceptualize and operationalize supply chain resilience (Akpan, Awe & Idowu, 2019, Oni, et al., 2018). These frameworks generally aim to offer structured guidance for building robust, adaptable, and sustainable supply networks. While early studies primarily focused on disruption risk management and business continuity planning, more recent models emphasize proactive capabilities such as adaptability, agility, and the use of digital technologies.

The evolution of supply chain resilience frameworks can be traced to multiple domains, including systems engineering, operations research, and organizational behavior. Notable frameworks include the Resilience Triangle Model, which evaluates performance degradation and recovery speed; the four-stage model encompassing readiness, response, recovery, and growth; and dynamic capabilities-based frameworks that highlight the importance of sensing, seizing, and reconfiguring resources (Akter & Wamba, 2019, Henke & Jacques Bughin, 2016). These models underscore the multidimensional nature of resilience and suggest that it must be embedded in the structural, operational, and strategic layers of the supply chain. In post-pandemic research, there has been a growing push toward integrating sustainability and digital transformation into resilience models, reflecting the broader shifts in global supply chain priorities (Oyedokun, 2019).

Five key dimensions consistently emerge in literature as foundational to supply chain resilience: redundancy, flexibility, responsiveness, collaboration, and digitalization. Redundancy involves maintaining surplus resources such as safety stock, backup suppliers, and additional production capacity. Though often criticized for being cost-inefficient, redundancy can be strategically leveraged to buffer against major disruptions (Awe, 2017, Oduola, et al., 2014). Flexibility refers to the ability to adapt production, sourcing, and logistics strategies in response to shifting conditions. This may involve flexible manufacturing systems, multi-skilled labor, or diversified supplier bases. Responsiveness is closely tied to speed and agility the capability to sense and react to disturbances in real time. High responsiveness is often facilitated by integrated information systems, predictive analytics, and real-time monitoring.

Collaboration is another vital dimension that enhances resilience by fostering trust, transparency, and shared risk management among supply chain partners. Collaborative practices include joint planning, supplier relationship management, and coordinated recovery efforts. Finally, digitalization plays a transformative role by enabling data-driven decision-making, process automation, and enhanced visibility across the supply chain. Technologies such as the Internet of Things (IoT), blockchain, artificial intelligence (AI), and digital twins are being increasingly incorporated to simulate disruptions, monitor performance, and facilitate agile responses (Awe & Akpan, 2017, Olaoye, et al., 2016). These five dimensions are not mutually exclusive but often interact synergistically, meaning that the presence of one can enhance the effectiveness of the others. However, balancing these elements with cost efficiency remains a central challenge for decision-makers.

In this context, Multi-Criteria Decision Analysis (MCDA) has emerged as a valuable tool for evaluating and optimizing resilience strategies in supply chain networks. MCDA provides structured methodologies for comparing alternatives based on multiple, often conflicting criteria, making it especially useful in complex decision environments like supply chain management. Techniques such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Elimination and Choice Expressing Reality (ELECTRE), and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) have been widely applied. These methods support the integration of qualitative expert judgments with quantitative data, allowing organizations to rank resilience strategies, assess trade-offs, and prioritize interventions (Al-Badi, Tarhini & Khan, 2018, Henkey, 2017, Wladdimiro, et al., 2018).

Several studies have applied MCDA to specific aspects of supply chain resilience. For instance, researchers have used AHP to determine the relative importance of resilience capabilities such as flexibility, visibility, and collaboration under various disruption scenarios. Others have employed TOPSIS to evaluate different supplier selection strategies based on resilience criteria like lead time variability, geographical risk, and inventory availability. PROMETHEE has been applied in optimizing facility location decisions by accounting for environmental and resilience indicators simultaneously. These applications demonstrate the versatility of MCDA in addressing multi-dimensional problems in supply chain design and operation (Mustapha, et al., 2018).

However, despite its utility, existing research on the application of MCDA to supply chain resilience remains fragmented and context-specific. Many studies focus narrowly on individual components such as supplier selection or transportation mode choice, without adopting a holistic view of the supply chain. Moreover, most existing models are developed using hypothetical data or limited case studies, reducing their generalizability (Shrivastava & Pal, 2017, Sun & Ma, 2012, Veenema, 2018). Another critical limitation is the inadequate integration of dynamic and real-time data, which is increasingly essential in rapidly changing environments. Few studies account for temporal variability in disruptions or use simulation-based approaches to validate MCDA models in real-world settings. Figure 1 shows figure of a Resilient Supply Chain Structure presented by Blos, Wee & Yang, 2012.

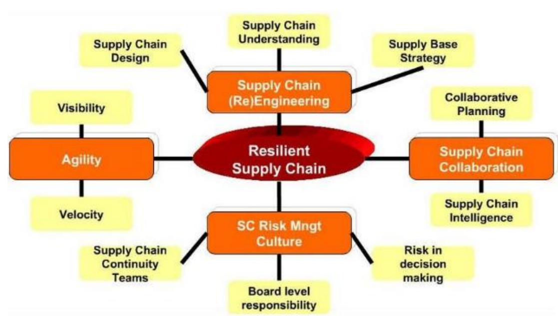

Figure 1: A Resilient Supply Chain Structure (Blos, Wee & Yang, 2012).

Furthermore, while the role of digitalization in enhancing supply chain resilience is well acknowledged, its incorporation into MCDA frameworks is still emerging. Most decision models do not adequately capture the impact of technologies such as AI-driven forecasting, blockchain-based traceability, or IoT-enabled asset tracking. There is also a lack of studies addressing the trade-offs between resilience and sustainability, especially in the context of carbon footprint, circular economy practices, and regulatory compliance. Given the heightened importance of environmental and social governance (ESG) goals, future research must integrate these aspects into MCDA frameworks to ensure alignment with broader organizational objectives (și Econometrie, 2018, Tabish & Syed, 2015, Wang, et al., 2016).

Another notable gap lies in the absence of stakeholder-centric approaches. Supply chain resilience is influenced by a range of actors, including suppliers, customers, regulators, and logistics providers. Yet, most MCDA applications assume a centralized decision-maker and do not capture the distributed nature of resilience-building efforts. Incorporating multiple stakeholder perspectives, possibly through participatory MCDA or multi-agent modeling, could enhance the robustness and acceptance of decision outcomes. Additionally, resilience indicators often lack standardization, leading to inconsistencies in how dimensions such as flexibility or collaboration are measured and compared across studies (Simchi-Levi, Wang & Wei, 2018, Thürer, et al., 2019).

The post-pandemic context also introduces new dimensions of uncertainty that existing MCDA models may not fully accommodate. These include geopolitical instability, health-related risks, labor shortages, and shifting consumer behaviors. Adapting MCDA tools to address these emerging risk vectors possibly through hybrid models that combine scenario planning, fuzzy logic, or system dynamics represents a promising direction for future inquiry.

In conclusion, while significant progress has been made in understanding and operationalizing supply chain resilience, there is a clear need for more integrated, data-rich, and technology-aware decision frameworks. The application of Multi-Criteria Decision Analysis offers a structured and flexible approach to support this endeavor. However, to fully realize its potential, MCDA models must evolve to capture the complexity, dynamism, and interconnectivity of modern supply chains. This includes bridging gaps related to stakeholder engagement, sustainability integration, real-time data usage, and technological innovation (Srinivasan, 2016, Umar, Wilson & Heyl, 2017, Yamada & Peran, 2017). A holistic, adaptable, and interdisciplinary approach will be essential to guide the development of resilient supply chain networks capable of withstanding future disruptions in an increasingly uncertain global environment.

2.2. Methodology

This study adopts a multi-criteria decision analysis (MCDA) approach to develop a resilient supply chain framework in the post-pandemic era. The methodology integrates insights from data-driven decision-making, disaster response logistics, and digital transformation in supply chain networks. Drawing from Abdalla & Esmail (2019) and Akter & Wamba (2019), the research incorporates disaster management principles and the role of big data in enhancing decision-making agility.

The study utilizes both primary and secondary data sources. Literature reviewed includes contributions from Chen et al. (2015), Blos et al. (2012), Ben-Daya et al. (2019), and Wang et al. (2016), addressing supply chain resilience, Internet of Things (IoT), and big data analytics. Key criteria for supply chain resilience—such as adaptability, visibility, robustness, and responsiveness—were identified from these sources.

Expert judgment and stakeholder consultations were employed to assign weights to the identified criteria using Fuzzy Best-Worst Method (F-BWM) as per Gan et al. (2019), accommodating the uncertainty and vagueness in human judgments. The alternatives, representing different supply chain configurations or recovery strategies, were then evaluated using GMo-RTOPSIS, a robust technique for ranking in uncertain environments.

To operationalize the analysis, software tools were used to implement the MCDA process, with data inputs structured around pre-pandemic and post-pandemic indicators as highlighted in Simchi-Levi et al. (2018) and Gligor et al. (2018). These include indicators like lead time volatility, supplier disruption rate, inventory recovery span, and digital integration level (Rejeb et al., 2019; Shah et al., 2019).

Validation of the model was conducted through simulation scenarios incorporating past disaster response cases and logistics stress tests, referencing frameworks from Canton (2019), Collier & Lakoff (2015), and Espinosa & Armour (2016). The simulated results were benchmarked against performance data from existing resilient networks in agri-food, healthcare, and manufacturing sectors (Barrett et al., 2019; Chen et al., 2015; Kumar et al., 2018).

The outcomes of the MCDA evaluation were visualized through decision matrices, ranking charts, and trade-off curves. These visual tools supported sensitivity analyses to test model robustness against changes in weight or criteria performance. Final recommendations prioritized supply chain models exhibiting high adaptability, digital responsiveness, and node redundancy. This ensures enhanced preparedness and continuity during systemic shocks in future crises.

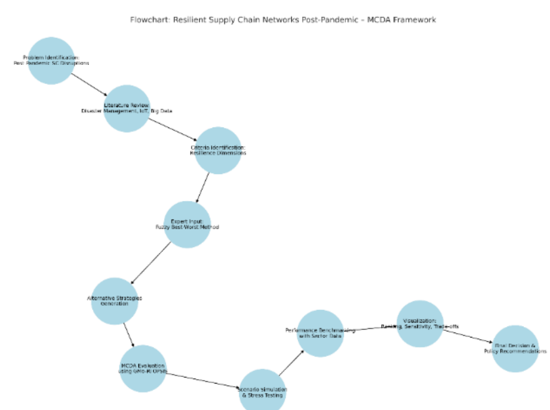

Figure 2: Flowchart of the study methodology

2.3. Model Development

The development of a robust and resilient supply chain network in the post-pandemic era requires a structured and systematic approach to decision-making, one that accommodates the complexities and uncertainties inherent in global supply chains. Multi-Criteria Decision Analysis (MCDA) provides a flexible framework for navigating these complexities by enabling the evaluation of multiple, often conflicting, criteria (Al-Badi, et al., 2012, Jha, 2010, Russom, 2011). To guide strategic decisions for resilience enhancement, this study employs a hybrid MCDA approach combining the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). This hybrid methodology allows for the derivation of relative importance weights and the ranking of alternative supply chain configurations under multiple evaluation criteria.

At the core of the model is a hierarchical decision structure that organizes the resilience problem into a logical and manageable framework. The hierarchy is designed in three levels: the overall goal at the top, the evaluation criteria and sub-criteria in the middle, and the alternative supply chain strategies at the bottom. The top level of the hierarchy is defined as the "Selection of Optimal Supply Chain Strategy for Post-Pandemic Resilience." This reflects the overarching aim of the model to identify the most suitable configuration that enhances supply chain resilience without compromising operational efficiency or sustainability (Aliyu, 2015, Kalisetty, 2017, Kapucu & Özerdem, 2011).

The second level of the hierarchy comprises the key criteria that influence supply chain resilience. These criteria are carefully selected based on literature review, expert consultations, and industry reports. The five main criteria include flexibility, redundancy, responsiveness, collaboration, and digitalization. Each of these is further decomposed into sub-criteria to capture specific operational and strategic dimensions. For example, flexibility includes production flexibility, logistics adaptability, and sourcing agility (Alsubaie, et al., 2014, Karaesmen, Scheller–Wolf & Deniz, 2010). Redundancy is assessed through sub-criteria such as safety stock, backup suppliers, and excess capacity. Responsiveness encompasses lead time, order fulfillment speed, and real-time data access. Collaboration includes information sharing, trust-based partnerships, and joint recovery planning. Digitalization is measured by the extent of technology adoption, use of analytics, and digital visibility across the supply chain.

To determine the relative importance of each criterion and sub-criterion, the AHP method is employed. AHP is a structured technique based on pairwise comparisons and expert judgment, which helps derive ratio-scale weights representing the priority of each element in the hierarchy. The process begins by developing pairwise comparison matrices for each set of criteria and sub-criteria. Experts, including supply chain managers, operations researchers, and logistics professionals, are asked to compare the elements based on their relative importance to post-pandemic resilience (Analytics, 2016, Kumar, Mookerjee & Shubham, 2018, Zaman, et al., 2014). These judgments are captured on a 1-to-9 scale, where 1 indicates equal importance and 9 indicates extreme importance of one element over another.

The collected pairwise comparison matrices are then processed to calculate normalized eigenvectors, which represent the priority weights of the criteria. Consistency ratios (CR) are computed to ensure the reliability of expert judgments. A CR value below 0.10 is generally considered acceptable, indicating a reasonable level of consistency. In cases where the consistency ratio exceeds this threshold, the judgments are reviewed and refined. Once the global weights of all sub-criteria are determined through aggregation, they are used as inputs for the subsequent TOPSIS analysis (Balan, 2018, Kwaramba, et al., 2019, Saban, 2014).

TOPSIS is employed to rank the alternative supply chain configurations based on their closeness to the ideal solution. The key advantage of TOPSIS lies in its ability to evaluate each alternative not in isolation, but in comparison with an ideal best-case and a worst-case scenario. The process begins by constructing a decision matrix where each alternative is assessed against all sub-criteria using either quantitative data or expert ratings. The decision matrix is then normalized to eliminate unit inconsistency and ensure comparability across criteria (Barrett, et al., 2019, Lee, 2018, Lei, et al., 2016). The criteria of resilient supplier selection under supply chain environment presented by Gan, et al., 2019 is shown in figure 3.

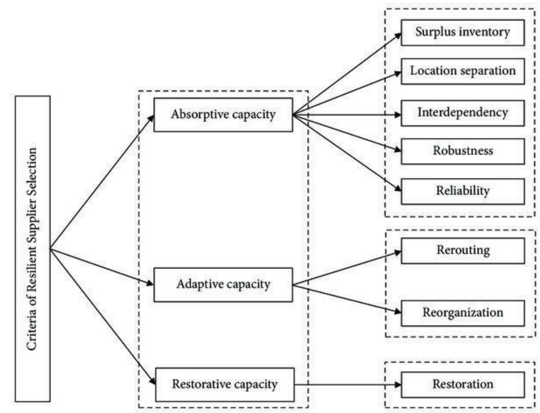

Figure 3: The criteria of resilient supplier selection under supply chain environment (Gan, et al., 2019).

Once normalized, the matrix is multiplied by the AHP-derived weights to obtain a weighted normalized decision matrix. This step integrates the relative importance of each criterion into the evaluation of alternatives. Following this, the positive ideal solution (PIS) and negative ideal solution (NIS) are identified. The PIS consists of the best value for each criterion (e.g., maximum flexibility, minimum lead time), while the NIS consists of the worst values. The Euclidean distance of each alternative from the PIS and NIS is then calculated.

The final step in the TOPSIS method involves computing the closeness coefficient (CC) for each alternative, defined as the ratio of its distance from the NIS to the sum of its distances from both the PIS and NIS. The alternatives are then ranked based on their CC values, with higher values indicating greater proximity to the ideal solution and thus a more resilient supply chain configuration (Ben-Daya, Hassini & Bahroun, 2019, Shah, et al., 2019).

In applying this model to a practical scenario, three supply chain strategies are considered: (1) a global centralized supply chain with low redundancy and high efficiency, (2) a hybrid supply chain combining global sourcing with regional production hubs, and (3) a localized, decentralized supply chain with higher redundancy and greater digital integration. Each strategy is evaluated using the developed AHP-TOPSIS framework.

The results indicate that the localized and hybrid configurations outperform the centralized model in terms of resilience. The localized model scores highly on flexibility, responsiveness, and digitalization due to its proximity to demand centers and investment in real-time visibility tools. The hybrid model, while not as flexible as the localized one, offers a balanced trade-off between cost efficiency and risk mitigation. Conversely, the centralized model, although efficient under stable conditions, performs poorly in responsiveness and redundancy, making it less suitable for post-pandemic realities (Canton, 2019, Lehmacher, 2017, Mangan & Lalwani, 2016). Umar, Wilson & Heyl, 2017 presented conceptual framework: Food supply chain resilience shown in figure 4.

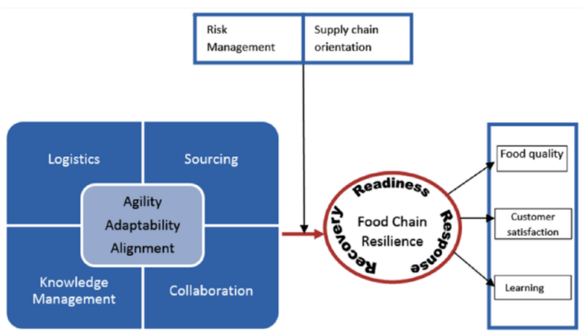

Figure 4: Conceptual framework: Food supply chain resilience (Umar, Wilson & Heyl, 2017).

Through this hybrid AHP-TOPSIS model, decision-makers gain a comprehensive tool for evaluating complex resilience trade-offs. The combination of expert-driven weight derivation and quantitative alternative ranking ensures that both subjective insights and objective data are incorporated into the decision-making process. Moreover, the model's hierarchical structure offers clarity in understanding how strategic choices impact different dimensions of resilience.

This model development highlights the importance of structured decision tools in guiding supply chain transformation efforts. By offering a systematic framework to assess resilience-enhancing strategies, it empowers organizations to make informed, transparent, and justifiable choices that align with both operational goals and risk management priorities. As global supply chains continue to face volatility and uncertainty, such models will play a critical role in ensuring preparedness, agility, and long-term sustainability (Chelleri, et al., 2015, March & Ribera-Fumaz, 2016).

2.4. Case Study Application

To demonstrate the practical application of the proposed Multi-Criteria Decision Analysis (MCDA) framework for evaluating resilient supply chain networks post-pandemic, a case study was conducted in the manufacturing sector, specifically within the consumer electronics industry. This industry was among the hardest hit by the COVID-19 pandemic due to its reliance on globalized supply networks, just-in-time production strategies, and a heavy dependence on critical components such as semiconductors. The disruption to supply chains originating in East Asia, compounded by international trade restrictions and transportation bottlenecks, led to massive backlogs in production and a significant loss of revenue for many manufacturers. As the industry seeks to reconfigure its operations to become more resilient, this case study provides valuable insights into the strategic decision-making process required to adapt supply chain structures to the new post-pandemic realities (Chen, et al., 2015, Marin Bustamante, 2019, Shih & Wang, 2016).

The organization selected for the study is a mid-sized electronics manufacturer operating across North America, Europe, and Asia. The company produces smartphones, tablets, and smart home devices and sources components such as circuit boards, batteries, and display units from suppliers across Asia and Eastern Europe. Its supply chain model before the pandemic prioritized cost-efficiency, relying on centralized manufacturing in China and limited redundancy in logistics and warehousing. In the aftermath of COVID-19, the company initiated a strategic review of its supply chain network to enhance its ability to withstand future disruptions and recover rapidly (Chua, et al., 2018, Meijer & Bolívar, 2016, Wang, Kung & Byrd, 2018). As part of this effort, the firm collaborated with academic researchers and supply chain consultants to implement the AHP-TOPSIS-based decision framework proposed in this study.

To operationalize the model, data was collected through a combination of expert interviews, internal company reports, and industry databases. A panel of 12 experts was formed, comprising the company's supply chain director, procurement officers, logistics managers, IT specialists, and external consultants. These experts provided insights into the performance of different supply chain strategies and helped define the evaluation criteria and sub-criteria based on their relevance to resilience in the consumer electronics sector. Experts also participated in pairwise comparisons as part of the AHP process and provided performance scores for the alternative configurations evaluated during the TOPSIS analysis (Collier & Lakoff, 2015, Mohanty, Jagadeesh & Srivatsa, 2013).

The decision framework adopted a three-level hierarchy, with the overarching goal being the selection of the most resilient supply chain strategy. Five main criteria were evaluated: flexibility, redundancy, responsiveness, collaboration, and digitalization. Each criterion was further broken down into sub-criteria, such as production flexibility, backup suppliers, lead time, information sharing, and technology integration. Three alternative supply chain strategies were identified for evaluation: (1) the pre-pandemic centralized global supply chain model (Alternative A), (2) a hybrid model incorporating regional production hubs with partial redundancy (Alternative B), and (3) a fully decentralized and digitally integrated supply chain focused on local sourcing and agile logistics (Alternative C) (De Vass, Shee & Miah, 2018, Mohanty, et al., 2013).

The implementation began with the AHP process to derive weights for the criteria and sub-criteria. Experts performed pairwise comparisons to express the relative importance of each factor in the context of resilience. For instance, responsiveness and flexibility were rated higher than cost-related concerns, reflecting a shift in priorities following the pandemic. The consistency ratios of the expert inputs were calculated to ensure reliability, all falling below the accepted threshold of 0.10 (Edgeman, 2013, Oliver, 2010, Papakostas, O'Connor & Byrne, 2016). The final normalized weights were then aggregated to form the global weights for each sub-criterion, providing a foundation for evaluating the alternatives.

Next, the TOPSIS method was applied using the performance scores assigned to each alternative across the weighted sub-criteria. These scores were based on a combination of historical performance data and expert estimations. For example, the centralized model scored high on cost-efficiency but low on redundancy and responsiveness. The hybrid model showed moderate scores across most dimensions, offering a balanced performance. The decentralized model, while associated with higher operational costs, received high scores in flexibility, responsiveness, and digitalization due to its use of local suppliers, cloud-based logistics platforms, and AI-driven demand forecasting (Eksoz, Mansouri & Bourlakis, 2014, Phillips-Wren, et al., 2015).

The weighted normalized decision matrix was constructed, and the positive ideal solution (PIS) and negative ideal solution (NIS) were identified. Each alternative's Euclidean distance from the PIS and NIS was calculated to determine the closeness coefficient (CC). The closeness coefficient values were as follows: Alternative A (centralized) – 0.42, Alternative B (hybrid) – 0.71, and Alternative C (decentralized) – 0.86. These results indicate that Alternative C, the decentralized and digitally integrated supply chain model, is closest to the ideal solution in terms of resilience. Alternative B, the hybrid model, also performed well and may be considered a viable transitional strategy. Alternative A, although efficient during stable conditions, ranked lowest due to its inflexibility and high vulnerability to disruptions (El Haimar, 2015, Osman, 2019, Pundir, Jagannath & Ganapathy, 2019).

The outcomes of the model were presented to the company's strategic decision-making board, which subsequently endorsed a phased transition toward the decentralized model, starting with the establishment of regional production facilities in North America and Europe and investing in digital infrastructure to support real-time data exchange across the supply chain. The company also initiated partnerships with local suppliers to increase sourcing agility and reduce lead times.

Beyond decision support, the implementation of the AHP-TOPSIS model also fostered greater cross-functional collaboration within the organization. By involving stakeholders from procurement, logistics, IT, and strategy, the company was able to ensure that resilience considerations were integrated into every layer of the supply chain. Furthermore, the transparency and repeatability of the model allowed for clear communication of priorities and rationale behind the selected strategy, enhancing internal alignment and stakeholder buy-in (Espinosa & Armour, 2016, Qadir, et al., 2016, Shah, et al., 2019).

This case study underscores the practical value of MCDA tools in facilitating structured, evidence-based decision-making for supply chain resilience. The hybrid AHP-TOPSIS approach proved effective in balancing multiple resilience dimensions and highlighting trade-offs that might not be immediately apparent through traditional decision-making methods. While the highest-ranked strategy was not the most cost-efficient, the model enabled the company to recognize the long-term value of resilience, particularly in terms of continuity, responsiveness, and customer satisfaction (Ferreira, Arruda & Marujo, 2018, Raj, et al., 2015).

In conclusion, the application of the AHP-TOPSIS framework in this manufacturing case demonstrated its utility in guiding post-pandemic supply chain transformation. By incorporating expert judgment, organizational data, and structured analysis, the model helped identify the most resilient strategy tailored to the firm's operational context and market demands. The findings not only informed immediate strategic actions but also laid the groundwork for future investments in digitalization and regionalization. As global supply chains face increasing uncertainty, tools like this will be essential in supporting organizations to design networks that are not only efficient but also resilient, adaptive, and future-ready.

2.5. Results and Discussion

The implementation of the Multi-Criteria Decision Analysis (MCDA) framework for evaluating resilient supply chain networks post-pandemic produced significant insights that highlight the evolving priorities and strategic directions in global supply chain management. The results of the AHP-TOPSIS model, applied to the consumer electronics manufacturing case, revealed clear distinctions in the performance of various supply chain configurations with respect to resilience. The decentralized and digitally integrated supply chain configuration emerged as the most resilient option, followed closely by a hybrid model that combined global sourcing with regional production hubs. The traditional, centralized supply chain configuration, which had previously dominated due to its cost-efficiency, ranked the lowest in terms of resilience (FutureScape, 2018, Ragini, Anand & Bhaskar, 2018, Yu, Yang & Li, 2018).

These findings reinforce a central observation that resilience is multidimensional and cannot be achieved by focusing on cost metrics alone. In fact, the analysis showed that some of the most resilient features such as sourcing flexibility, real-time visibility, and redundancy often incur higher upfront costs but deliver superior long-term value through increased adaptability and risk mitigation. The highest-ranking supply chain model, which emphasized decentralization and digital integration, performed exceptionally well in flexibility, responsiveness, and digitalization (Gligor, Tan & Nguyen, 2018, Rathore, et al., 2016). This configuration relied on localized sourcing strategies, investments in predictive analytics, and the use of technologies like cloud-based logistics platforms and blockchain for traceability. These elements collectively enhanced the supply chain's ability to detect disruptions early, respond swiftly, and recover with minimal impact.

In contrast, the centralized model, while operationally efficient under stable conditions, was highly vulnerable to disruptions. It lacked redundancy, had limited flexibility due to long lead times and single-sourcing dependencies, and suffered from poor responsiveness. This trade-off between efficiency and resilience was a central theme in the analysis. While lean and cost-focused supply chains may optimize for profit margins in the short term, they often lack the robustness needed to survive shocks such as pandemics, geopolitical conflicts, or natural disasters (Grover, et al., 2018, Ratzesberger & Sawhney, 2017). The hybrid model provided a balanced compromise, offering moderate levels of resilience while still preserving some efficiency benefits. It demonstrated that resilience and efficiency need not be mutually exclusive, especially when supported by data-driven planning and regional risk diversification.

Digitalization emerged as a foundational pillar of resilience, cutting across all criteria and influencing every stage of the supply chain. The results showed that supply chains that had adopted digital technologies such as real-time inventory tracking, AI-driven demand forecasting, and automated risk monitoring had greater visibility into their operations and were better equipped to make proactive decisions. Digital platforms enabled end-to-end integration, improved supplier communication, and facilitated agile responses to disruptions. For instance, in the decentralized model, the use of digital twins allowed the company to simulate different disruption scenarios and test contingency plans, leading to faster recovery times and improved resource allocation. Moreover, digitalization supported collaboration by enabling shared dashboards and seamless information exchange among partners (Gunawardena, Shee & Miah, 2018, Rejeb, Keogh & Treiblmaier, 2019).

Localization also played a crucial role in enhancing resilience, especially in areas such as sourcing and manufacturing. By relocating production facilities closer to major consumer markets and diversifying supplier bases across regions, the company reduced its exposure to single points of failure and transportation bottlenecks. Localization also allowed for shorter lead times, faster decision-making, and reduced reliance on long-haul logistics networks, which had proven highly unreliable during the pandemic. Importantly, the model demonstrated that localized supply chains, when combined with advanced digital capabilities, could compete effectively with global models not only in resilience but also in responsiveness and customer satisfaction.

The practical implications of these findings are significant for both supply chain managers and policymakers. For supply chain managers, the results underscore the need to reevaluate traditional performance metrics and adopt a more holistic view of value creation. Rather than focusing exclusively on cost savings, managers must consider resilience as a strategic capability that supports long-term competitiveness. This includes investing in flexible manufacturing systems, developing relationships with multiple suppliers, and adopting digital tools that enhance visibility and coordination. Supply chain leaders must also build organizational cultures that support proactive risk management, scenario planning, and continuous learning.

Policymakers, on the other hand, have a critical role to play in enabling and encouraging the transition toward more resilient supply chains. The findings suggest that public policies can support resilience by incentivizing domestic manufacturing, funding digital infrastructure, and encouraging industry-wide standards for data interoperability and supply chain transparency. Governments can also facilitate resilience through trade diversification agreements, workforce upskilling programs focused on digital technologies, and national stockpiles for critical materials. Furthermore, collaboration between public and private sectors is essential to build resilient ecosystems, particularly in industries such as healthcare, semiconductors, and energy, where supply chain failures can have severe national and global consequences (Drew, 2015, Miller, 2015, Waite & McDonald, 2019).

Another important implication from the study is the value of structured decision-making tools like AHP-TOPSIS in navigating complex supply chain challenges. The ability to transparently assess multiple criteria, incorporate expert judgment, and quantify trade-offs allows organizations to make more informed and defensible decisions. In the context of post-pandemic recovery, where uncertainty remains high and resources are constrained, such tools can be especially valuable in guiding strategic investments. For instance, the model can be used to prioritize capital expenditures for supply chain transformation, evaluate the resilience of new suppliers, or assess the benefits of adopting new digital platforms.

The broader lesson from this analysis is that resilience must be designed into supply chains from the outset it cannot be an afterthought or a reactive measure. The pandemic has shown that global supply chains are increasingly exposed to a wide array of risks, from health crises and geopolitical tensions to climate-related events and cyber threats. As such, resilience must be embedded as a core design principle alongside traditional concerns like cost, speed, and quality. This requires a mindset shift across all levels of the organization and the development of new capabilities in areas such as data analytics, cross-functional collaboration, and strategic scenario planning.

Ultimately, the study affirms that resilient supply chains are not only better prepared for disruptions but also more adaptive, innovative, and aligned with stakeholder expectations in an era of growing scrutiny on corporate responsibility and risk governance. Organizations that embrace resilience as a strategic priority will be better positioned to navigate uncertainty, seize new opportunities, and build lasting competitive advantage. As the global economy continues to recover and adapt to the realities of a post-pandemic world, the insights from this research provide a roadmap for building supply chains that are not only efficient but also robust, responsive, and future-ready.

2.6. Sensitivity Analysis

The sensitivity analysis conducted for the Multi-Criteria Decision Analysis (MCDA) model used in evaluating resilient supply chain networks post-pandemic serves as a critical step in validating the robustness, reliability, and practical applicability of the proposed decision framework. While the hybrid AHP-TOPSIS model effectively ranks supply chain alternatives based on resilience criteria, it is essential to understand how sensitive the results are to variations in decision inputs particularly the weights assigned to criteria and the subjective judgments of experts. Additionally, testing the model under different hypothetical disruption scenarios helps to determine whether the recommendations hold true in dynamic and uncertain operating conditions (Drew, 2015, Miller, 2015, Waite & McDonald, 2019).

To begin with, an examination of the model's robustness to weight changes was performed by systematically varying the weights assigned to the primary criteria: flexibility, redundancy, responsiveness, collaboration, and digitalization. These weights, initially derived from the AHP process based on expert consensus, represent the relative importance of each criterion in assessing supply chain resilience. However, real-world decision-making often involves uncertainty in weight assignment due to evolving priorities or limited information. To test the model's stability, the weights were incrementally adjusted by ±10%, ±20%, and ±30% from their baseline values, and the resulting rankings of the supply chain alternatives were observed.

The analysis revealed that while minor variations in weights had limited effect on the overall rankings, more substantial deviations particularly those affecting responsiveness and flexibility led to changes in the relative positions of the hybrid and decentralized alternatives. Interestingly, the centralized model consistently ranked lowest across all tested weight scenarios, reinforcing the conclusion that it lacks resilience under diverse conditions. The decentralized model, which was initially the top-ranked configuration, remained robust in most variations, particularly when responsiveness and digitalization maintained high importance (Drew, 2015, Miller, 2015, Waite & McDonald, 2019). However, in scenarios where redundancy was heavily weighted, the hybrid model occasionally outperformed the decentralized model, due to its moderate level of built-in redundancies without the cost overhead of full localization. This outcome highlights the model's responsiveness to shifts in strategic emphasis, confirming its value as a flexible decision support tool that adapts to evolving resilience priorities.

The impact of varying expert preferences was another critical element of the sensitivity analysis. Since the AHP method relies on subjective pairwise comparisons provided by domain experts, differences in experience, role, and organizational context can influence the derived weights and decision outcomes. To explore this dimension, the expert panel was segmented into three groups: supply chain operations professionals, IT and digital transformation specialists, and executive-level decision-makers. Each group conducted the AHP pairwise comparisons independently, producing three distinct sets of weights. These weights were then used in the TOPSIS model to evaluate the supply chain alternatives and compare the resulting rankings.

The results demonstrated notable variations in preferences across the groups. The operations professionals emphasized flexibility and redundancy, prioritizing structural robustness and buffer capacity as key attributes of resilience. In contrast, IT specialists assigned higher importance to digitalization and responsiveness, reflecting their focus on data-driven agility and visibility. Executive-level decision-makers balanced long-term strategic goals with short-term operational needs, giving relatively equal weight to collaboration, flexibility, and digitalization (Dougherty & Lombardi, 2016, Sithole, et al., 2017). Despite these differences in weighting, the decentralized model emerged as the preferred option in two out of the three expert groups, with the hybrid model being the top choice among the executives. These variations underscore the importance of capturing diverse perspectives in resilience planning and validate the model's ability to accommodate different stakeholder views without compromising analytical rigor.

To further stress-test the model's robustness, a scenario-based analysis was conducted to simulate future disruptions that might impact global supply chains. Three plausible disruption scenarios were developed based on recent trends and expert projections: (1) a geopolitical conflict leading to trade route closures and supplier embargoes, (2) a climate-related disaster affecting key logistics hubs and infrastructure, and (3) a cyber-attack that cripples digital communication and supply chain management systems. Each scenario was characterized by its unique impact on specific criteria and sub-criteria (Chong, 2019, McDonald, 2016, Watters & Christensen, 2014). For example, in the geopolitical scenario, redundancy and localization became more critical due to limited global access. In the climate disaster scenario, flexibility and responsiveness were prioritized to enable fast rerouting and adaptation. In the cyber-attack scenario, the importance of digitalization was downplayed due to the temporary failure of digital infrastructure, and collaboration took on added significance.

For each scenario, the criteria weights were adjusted to reflect the new risk environment, and the AHP-TOPSIS model was re-run to observe how the rankings of supply chain alternatives shifted. In the geopolitical disruption scenario, the decentralized model solidified its position as the top-ranked strategy due to its reliance on local suppliers and diversified production capabilities. In the climate disaster scenario, the hybrid model gained prominence because of its ability to pivot operations across regions, offering a balance between flexibility and redundancy. In the cyber-attack scenario, the decentralized model lost ground due to its dependence on interconnected digital systems, while the hybrid model emerged as more resilient due to its compartmentalized operations and stronger emphasis on partner-based recovery.

These scenario analyses provide two critical insights. First, resilience is context-dependent, and no single supply chain configuration is universally optimal under all conditions. Second, the flexibility of the MCDA model allows it to adapt to changing external pressures and strategic objectives by recalibrating criteria weights and evaluating alternative outcomes. This adaptability is particularly important in a post-pandemic world where the nature of supply chain disruptions is increasingly multifaceted and dynamic (Bybee, 2013, Masten, 2011, Walsh, 2015).

From a decision-making perspective, the findings from the sensitivity analysis reinforce the need for proactive and iterative resilience planning. Supply chain managers should not treat resilience strategies as static solutions but rather as evolving constructs that must be regularly reassessed in light of new risks, technologies, and stakeholder expectations. The MCDA framework, by supporting scenario analysis and stakeholder input, provides a structured mechanism for such periodic evaluations. It also serves as a powerful communication tool that helps align cross-functional teams around shared priorities and evidence-based recommendations.

Moreover, the sensitivity analysis highlights the strategic value of investing in decision support systems that integrate real-time data feeds and allow for rapid reconfiguration of inputs. In environments characterized by high uncertainty, the ability to quickly assess the implications of new developments and adjust course accordingly can differentiate resilient organizations from vulnerable ones. As supply chains become more digitized and interconnected, incorporating adaptive decision models into enterprise resource planning (ERP) and supply chain management (SCM) platforms can provide a significant competitive advantage (Masoomi & van de Lindt, 2019).

In conclusion, the sensitivity analysis validates the robustness, flexibility, and practical utility of the hybrid AHP-TOPSIS framework in guiding resilient supply chain design. By testing the model across variations in weights, expert perspectives, and disruption scenarios, the study confirms that the model produces consistent and actionable results under diverse conditions. It demonstrates the importance of accommodating uncertainty and stakeholder diversity in resilience planning and provides a scalable approach to evaluate and improve supply chain configurations over time. As organizations continue to navigate the complexities of the post-pandemic landscape, decision tools that support adaptability, inclusivity, and scenario-based reasoning will be essential to building supply chains that are not only efficient and responsive but also resilient, future-proof, and strategically aligned.

2.7. Conclusion

This study has presented a comprehensive analysis of resilient supply chain networks in the post-pandemic context through the development and application of a Multi-Criteria Decision Analysis (MCDA) framework. By integrating the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the research offers a structured, data-driven methodology to evaluate and rank alternative supply chain configurations based on key resilience dimensions. The core contributions include the identification of critical criteria flexibility, redundancy, responsiveness, collaboration, and digitalization that influence supply chain resilience, as well as the demonstration of a practical decision-support model using a real-world case study in the consumer electronics manufacturing sector. Through expert input, performance scoring, and scenario-based sensitivity analysis, the model facilitated an informed comparison of centralized, hybrid, and decentralized supply chain strategies.

The findings underscore the growing importance of MCDA in supply chain decision-making, especially in environments marked by volatility, uncertainty, and complex trade-offs. Unlike traditional cost-centric approaches, the MCDA framework enables decision-makers to incorporate qualitative judgments, strategic priorities, and quantitative data into a transparent and defensible evaluation process. Its capacity to weigh multiple, often conflicting objectives makes it particularly suited to post-pandemic decision contexts where organizations must balance efficiency with resilience, agility with sustainability, and cost control with risk mitigation. The hybrid AHP-TOPSIS model, in particular, proved effective in guiding strategic decisions, highlighting the value of flexibility and responsiveness, and reinforcing the role of digitalization and localization in modern supply chain design.

Despite its strengths, the study is not without limitations. The model relies on expert judgments, which, although structured and validated for consistency, remain inherently subjective. The selection of criteria and sub-criteria, while comprehensive, may not capture all dimensions relevant to other sectors or geographic regions. Additionally, the case study focused on a single industry, which may limit generalizability. The reliance on static weights and discrete alternatives also does not fully account for dynamic changes in the external environment or continuous decision-making processes.

Future research should explore the integration of real-time data feeds and machine learning algorithms into MCDA frameworks to support dynamic and automated decision-making. Expanding the model to include environmental and social sustainability metrics would also enhance its relevance in the era of ESG accountability. Further validation across multiple industries and global contexts is recommended to increase generalizability and robustness. Additionally, participatory approaches that involve a wider range of stakeholders including suppliers, customers, and policymakers could enrich the decision-making process and promote collaborative resilience strategies. Overall, this study contributes a practical, adaptable, and forward-looking framework for building supply chain networks that are equipped to navigate an increasingly unpredictable global landscape.

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