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Industry 4.0-Enabled Sustainable Supply Chain Strategies: Insights from the Emerging Garments Industry Using a Bayesian Best-Worst Method

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Abstract

Industry 4.0 (I4.0) technologies are diffusing quickly in making export oriented garment supply chains, particularly in developing economies such as Bangladesh and India. The latest technologies of IoT, robotics, cloud, AI-driven analytics and blockchain are set to introduce more effective operations, supply chain optimization, and sustainability. But adoption is spotty as infrastructure gaps, financial limitations and a shortage of skills have been issues. This research fills the gap in systematically prioritizing the adoption criteria of I4.0 based on three core dimensions, including: Technological Readiness, Supply chain and Sustainability, using Bayesian Best-Worst Method (BWM). The analysis demonstrates that the most important drivers of performance have been: “Technology Readiness to Smart Integration,” at the company level; “Supply Chain Efficiency to Real-Time Visibility,” at the sector level, and “Sustainability-Driven Digital Compliance” at the industry level. These findings emphasize the need to build technological infrastructure and automate the processes to be able to support digital operations in clothing manufacturing. The paper can be of great benefit to decision-makers in terms of prioritizing on technology investments depending on the unique needs of the ready-made garments industry; hence, enhancing competitiveness and sustainability. The study provides sound, uncertainty-sensitive ordering through the application of the BWM, and contributes to the maturity of the methodology of digital transformation of global garment supply chains.

Keywords: Industry 4.0 adoption criteria, export-oriented garment supply chains, Bayesian Best Worst Method (BWM), Technology Readiness, Supply chain efficiency, Ready Made garments(RMG), multi criteria decision making.

1. Introduction

The export-oriented garment supply chain is at the forefront of global manufacturing,characterized by fierce competition, rapidly changing consumer demands and increasing pressure to enhance efficiency, transparency and sustainability (Abdul & Sohag, n.d.; Mim et al., 2024a). One of the biggest industries in the world, the textile sector makes an immense economic contribution especially in developing countries like Bangladesh, China and India(Abbate et al., 2024; Salman et al., 2024) . Both skilled and unskilled persons can find work in these industries (Islam & Halim, 2022; Khan et al., 2025). As a developing country, the ready-made garment (RMG) sector of Bangladesh is also in the line of slow adoption (Wasik, n.d.). The RMG sector of Bangladesh has around 11.2% contribution to the gross domestic product (GDP) of this country (Glogar et al., 2025; Salman et al., 2024).

The worldwide transition towards smart, digitalized manufacturing is fundamentally reshaping the landscape for export-oriented garments. Industry 4.0 (I4.0), anchored in technologies like modular and robotic sewing lines, advanced automation, IoT driven sensing, real time RFID tracking, cloud based ERP integrations and blockchain enabled traceability offers unparalleled opportunities to enhance quality , compliance and sustainable supply chain performance(Islam & Halim, 2022; Mim et al., 2024b). For the RMG industry, embracing these innovations is not merely a strategic advantage but a necessity for fulfilling strict requirements for buyers and supporting circular economy outcomes (Abbate et al., 2024; Glogar et al., 2025).

However, the pathway to effective I4.0 implementation in garment supply chains is challenged by significant barriers, including limited technological readiness, infrastructure deficiencies, high initial investment, workforce skill gaps and fragmented supply chain visibility (Abdul & Sohag, n.d.; Khan et al., 2025). Technology Readiness manifested in the deployment of modular and robotic sewing lines and advanced sensing and inspection systems plays a pivotal role in enhancing flexibility, quality control and resource efficiency within garment production (Asrol, 2024; Salman et al., 2024). In parallel, horizontal integration via cloud based ERP and blockchain-enabled traceability solutions significantly improve process transparency, supplier connectivity and compliance with buyer requirements (Mim et al., 2024a; Singh et al., 2025a). IoT and RFID based asset tracking further drive real time visibility and accuracy in production and warehousing, supporting swift responses to dynamic supply conditions(Abbate et al., 2024; Islam & Halim,2022). From a supply chain and production efficiency perspective, the adoption of AI enabled planning, smart replenishment, cost efficient warehousing and digitalized export compliance has been logically linked to improved on time delivery rates, lower operational costs and better sustainability metrics (Glogar et al., 2025). Yet, the realization of these benefits across the industry remains uneven, highlighting the need for a systematic decision making framework to prioritize investments, maximize ROI and build resilience for global competition and regulatory demands(Khan et al., 2025). To respond to these challenges, this study employs the Bayesian Best-Worst Method (BWM), a proven multi criteria decision making approach; to systematically prioritize I4.0 adoption criteria for export-oriented garment supply chains, where the research aims to inform strategic decision making and guide the structured digital transformation required to sustain global competitiveness in the RMG sector (Salman et al., 2024). The study seeks to answer the following research questions:

RQ1. Which specific industry 4.0 adoption criteria, within the domains of technology readiness and supply chain/ production efficiency, are most critical to enhancing performance in export oriented garment supply chains?
RQ2. How can the Bayesian Best-Worst Method be effectively applied to analyze and consider the industry's resource limitations and strategic imperatives to assign priorities to these I4.0 adoption criteria?

RQ3. Based on prioritized criteria, what strategic pathways and recommendations can be formulated to guide phased adoption and sustained competitiveness in the global garment export market?

To address these research questions, this study contributes to the literature and practice of digital transformation in export-oriented garment supply chains by identifying key Industry 4.0 adoption criteria and drivers in the RMG context(Mim et al., 2024b). To prioritize these criteria, the Bayesian Best-Worst Method (BWM) is employed, integrating expert knowledge and stakeholder perspectives(Wasik, n.d.). The approach derives a ranked set of Industry 4.0 adoption priorities aligned with the strategic objectives of export-oriented manufacturers. The remainder of the article is organized as follows, Section 2 reviews the relevant literature and background on industry 4.0 digital transformation and multi criteria decision making in the context of garment supply chains. Section 3 presents the research methodology, detailing the steps of the Bayesian BWM application and expert input process. Section 4 discusses the results, including analysis of the prioritized criteria and their implications for the industry. Section 5 offers managerial and strategic recommendations based on the findings whereas Section 6 concludes the article, highlighting limitations and routes for future research.

2. Literature Review

2.1 Industry 4.0 and Export-Oriented Garment Supply Chains

The global garment supply chain, especially in emerging economies such as Bangladesh, India, and China, is undergoing transformative shifts driven by Industry 4.0 (I4.0) technologies(Mim et al., 2024c). Characterized by automation, smart robotics, IoT-enabled tracking, cloud data integration, and blockchain traceability, these innovations empower manufacturers to improve supply chain agility, transparency, and sustainability (Munim et al., 2022). However, despite the growing relevance of I4.0, adoption within the ready-made garment (RMG) sector of Bangladesh remains uneven and challenged by technological readiness gaps, infrastructure deficits, and workforce skill shortages (Lahdhiri et al., 2022).

2.2 Technological Drivers of Industry 4.0 Adoption

Critical technological enablers include modular and robotic sewing lines, AI-based analytics, digital twins, advanced cloud computing, and additive manufacturing techniques (Debnath et al., 2023a).Robotics and Automated Guided Vehicles (AGVs) enhance operational throughput and labor productivity while enabling workplace safety in pandemic contexts(Rahman et al., 2023). Digital twins provide virtual factory simulations to optimize processes and reduce downtime, whereas cloud and big data platforms streamline real-time data sharing across supply networks(Genovese et al., 2017) .Furthermore, blockchain facilitates end-to-end product traceability and compliance validation, increasingly demanded by international buyers (Mim et al., 2024c).

2.3 Supply Chain and Production Efficiency Enhancements

Adoption of vendor-managed inventory (VMI), collaborative supply chain management, and demand-driven production models integrates lean and agile manufacturing principles to reduce lead times, minimize waste, and enhance responsiveness (Singh et al., 2025b). Smart replenishment systems and real-time digital supply chain visibility, enabled by IoT and RFID, improve inventory accuracy and reduce risks of disruption (Lahdhiri et al., 2022).

Optimization strategies targeted at port logistics and compliance processes further strengthen export reliability and cost efficiency (Debnath et al., 2023a).

2.4 Sustainability and Circular Economy Integration

Sustainability dimensions encompass green warehousing, eco-friendly component sourcing, and enhanced waste and emission controls, supporting the circular economy framework within the sector (Rahman et al., 2023). Renewable energy adoption in manufacturing operations aligns with international buyer policies, reducing carbon footprints and operational risks (Genovese et al., 2017). Ethical labor compliance and social responsibility further underpin sustainable market positioning (Govindan et al., 2015a).Innovations in packaging and reverse logistics promote resource recirculation through take-back schemes, reinforcing closed-loop supply chain economics(Mim et al., 2024c) .

2.5 Challenges and Gaps in Industry 4.0 Adoption

While Industry 4.0 technologies hold promise to revolutionize the RMG supply chain, factors such as high capital investment requirements, fragmented digital infrastructure, and limited human capital readiness impede widespread implementation (Munim et al., 2022).The dynamic nature of global buyer expectations necessitates a rigorous prioritization framework to allocate scarce resources effectively, an area where methodological gaps persist (Salman et al., 2025a).

2.6 Research Contributions and Methodological Approaches

Addressing these needs, the Bayesian Best-Worst Method (BWM) has emerged as a robust decision-support tool that incorporates expert knowledge to rank and prioritize I4.0 adoption criteria under uncertainty (Debnath et al., 2023a).While studies in pharmaceutical and other manufacturing sectors have utilized the BWM and related method, its application within the RMG supply chain context remains scant (Fahim Faisal et al., n.d.). This study thus fills a critical gap, integrating technological, supply chain, and sustainability drivers into a unified prioritization framework tailored for Bangladeshi RMG manufacturers (Nwakuchi et al., n.d.).

Table 1. Drivers and Technologies for Implementing Industry 4.0 in Export-Oriented Garment Supply Chains

Context	Sl.	Drivers	How does it affect the garment industry/supply chain	References
Technological Readiness	1	Robots or Automated Vehicles (AGVs)	Automates material handling, increases throughput, reduces labor dependency, and supports social distancing during disruptions like pandemics.	(Debnath et al., 2023b; Govindan et al., 2015a; Rahman et al., 2023)
	2	Advanced Analytics and AI	Enables predictive quality control, demand forecasting, and production optimization for improved responsiveness and reduced errors.	(Govindan et al., 2015a; Nwakuchi et al., n.d.; Rahman et al., 2023)
	3	Digital Twin Technology	Simulates manufacturing for real-time process optimization, rapid reconfiguration, and downtime reduction.	(Govindan et al., 2015a; Nwakuchi et al., n.d.; Rahman et al., 2023)
	4	Robotic Sewing Lines	Enables continuous, high-precision operation, reduces defect rates and bottlenecks, and enhances stitching quality.	(Debnath et al., 2023b; Rahman et al., 2023)

	5	Cloud Computing & Big Data Platforms	Centralizes real-time data and analytics, enabling smarter planning, monitoring, and transparency across the supply network.	(Munim et al., 2022; Nwakuchi et al., n.d.)
	6	Additive Manufacturing (3D Printing)	Facilitates rapid prototyping/sample development, reduces time-to-market and wastage, and supports customization.	(Debnath et al., 2023a; Nwakuchi et al., n.d.)
	7	Blockchain	Provides end-to-end traceability, trust in compliance, digital certifications, and automation of documentation across partners.	(Genovese et al., 2017; Nwakuchi et al., n.d.)
	8	IoT Sensors and RFID	Real-time monitoring of goods, inventory, and assets, enhancing inventory control and enabling smart automation.	(Genovese et al., 2017; Rahman et al., 2023)
Supply Chain & Production Efficiency	9	Vendor Managed Inventory (VMI)	Empowers suppliers to remotely manage buyers' stock, reducing stockouts, supporting lean inventory, and improving responsiveness.	(Lahdhiri et al., 2022; Singh et al., 2025b)
	10	CRP / Smart Replenishment	Data-driven automated replenishment optimizes stock and minimizes supply interruptions and lead times.	(Lahdhiri et al., 2022; Singh et al., 2025b)
	11	Collaborative Supply Chain Management	Integrates planning and data sharing to increase resiliency, flexibility, and reliability across RMG supply chains.	(Debnath et al., 2023a; Govindan et al., 2015a)
	12	Lead Time Reduction to Port/Buyer	Digital optimization shortens order-to-export and order-to-delivery cycles, improving market responsiveness.	(Singh et al., 2025b)
	13	Digital Supply Chain Visibility	Enables accurate order fulfillment and quick issue resolution via real-time (IoT, ERP) tracking; boosts trust with buyers.	(Debnath et al., 2023a; Munim et al., 2022)
	14	Demand Driven Production (Lean-Agile Hybrid)	Matches production to actual market demand, minimizes overstock, and mitigates financial risk.	(Debnath et al., 2023b; Lahdhiri et al., 2022; Munim et al., 2022)
	15	Automated Quality Control & Defect Detection	In-line digital checking increases efficiency, reduces errors, and enhances throughput and speed.	(Munim et al., 2022; Rahman et al., 2023)
Sustainability & Supply Chain	16	Green Warehouse Practices	Implements energy-saving storage and eco-smart logistics, reducing costs and supporting green certifications.	(Debnath et al., 2023a; Govindan et al., 2015a)
	17	Sustainable Component Sourcing	Utilizes certified/recycled/organic materials for compliance with buyer requirements and enhances reputation.	(Debnath et al., 2023a; Govindan et al., 2015a)
	18	Waste & Emission Reduction	Digital monitoring and cleaner processes cut costs, meet stricter regulations, and support sustainability.	(Debnath et al., 2023a; Govindan et al., 2015a)
	19	Circular Economy & Recycling	Platforms for post-consumer returns enable garment/material recycling and closed-loop supply chains.	(Debnath et al., 2023b)
	20	Renewable Energy Adoption in Supply Chain	Adoption of renewable energy reduces environmental impact and aligns with global procurement policies.	(Debnath et al., 2023a; Govindan et al., 2015a)

21	Ethical Labor & Compliance Monitoring	Digital compliance auditing increases transparency, speeds remediation, and meets global buyer demands for traceability.	(Rahman et al., 2023)
22	Eco-Friendly Packaging & Logistics	Eco-materials, improved logistics, and digital tracking lower waste, disposal fees, and support circularity.	(Munim et al., 2022)
23	Reverse Logistics & Take-Back Programs	Enables efficient product returns for recycling/reuse, reducing raw material need and supporting full circular models.	(Lahdhiri et al., 2022)

3. Methodology

The Bayesian Best-Worst Method (BWM) framework was used in this study to assess the main drivers for applying Industry 4.0 methods in export-oriented clothing supply chains. The data collection process was structured in two main stages involving industry experts and academic professors. 21 experts were given a structured questionnaire in the first step with the aim of validating, improving, and classifying the drivers that had been initially chosen for further analysis. Out of these, 15 experts responded, yielding a response rate of 75%. The purposive sampling method, also known as judgmental or selective sampling, was applied in this stage. Unlike random sampling methods, purposive sampling involves the deliberate selection of participants based on criteria directly relevant to the research objectives (Palit et al., 2022; Ali et al., 2022). The selected experts had extensive professional engagement in the garment industry, with experience in Industry 4.0 technologies, supply chain management, sustainability initiatives, and digital transformation projects. They were chosen based on criteria such as a minimum of seven years of industry experience, academic or professional background in manufacturing and supply chain management, involvement in technology adoption initiatives, and participation in sustainable development practices. This approach ensured a broad range of perspectives, minimized potential bias, and provided a well-rounded representation of expert opinions. **Table 5 in Appendix** offers a synopsis of the profiles of the experts who took part in the research.

In the second stage, the 18 experts who participated in the initial survey were invited to complete a BWM survey form to establish the “Best-to-Others” and “Others-to-Worst” matrices. A total of 15 experts responded, representing a response rate of 83.3%. The responses were then processed using the Bayesian BWM method, which enabled the estimation of final weights of the identified drivers and their corresponding credal rankings. The results were subsequently shared with the experts for validation, and feedback confirmed the robustness of the findings.

The methodological framework of this research is illustrated in **Figure 1**. Following the analysis, the identified drivers were systematically organized into three main clusters: *Technological Readiness*, *Supply Chain and Production Efficiency*, and *Sustainability and Circular Economy*. The detailed classification of these clusters along with their respective drivers is presented in **Table 1.**

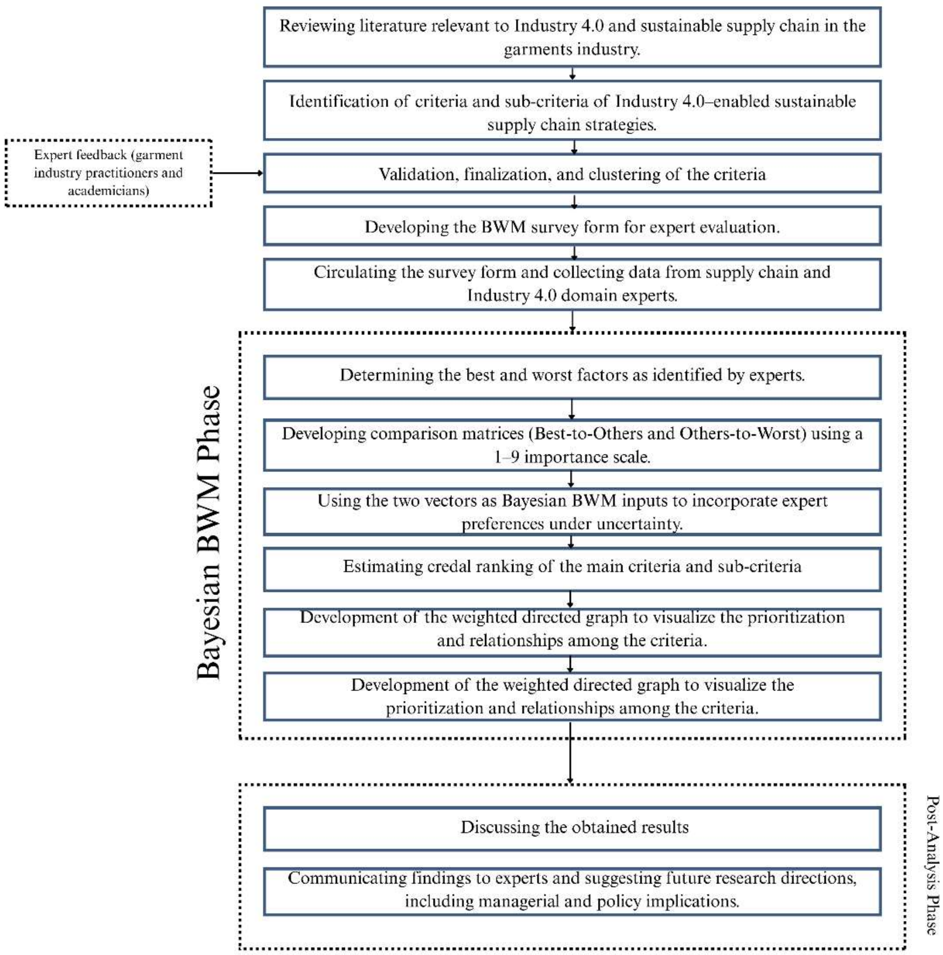

Figure 1: Methodological Framework

3.1 MCDM Method :

Multi-criteria decision-making (MCDM) is a sub branch of Operation Research. Its growth has rocketed continuously since its establishment. A particular MCDM problem includes several alternatives. These alternatives are then evaluated based on several criteria and on the elicitation of preferences of a decision maker (DM). This commonly results in sorting, ranking, or selecting the alternatives. In order to do the evaluation, we need to find the performance matrix (performance of the alternatives with respect to the criteria), and the importance (weight) of the criteria followed by simple and crucial data collection approach. Weight determination usually requires DM's preference. There are a number of methods to elicit preferences to determine the weights of the decision criteria from the DM, such as the analytic hierarchy process (AHP), the analytic network process (ANP), the simple multi-attribute rating technique (SMART), Swing, FARE, CILOS and IDOCRIW, etc(Mohammadi & Rezaei, 2020).

3.2 Bayesian Best-Worst Method

Best Worst Method (BWM) is one of the most efficient and relatively easy method for pairwise comparison since it can reduce the amount of inconstancy in the comparison to data from suveys. Bayesian Best Worst Method (BBWM), a modified and upgraded version of BWM for group decision-making, is an MCDM approach, where the perceptions of many experts are combined using a probabilistic approach, facilitating more precise decision-making about the integrated ranking of the criteria under consideration(Debnath et al., 2023b) . Unlike the traditional BWM, the Bayesian BWM technique minimizes information losses during group decision-making . The newly developed BWM minimizes information loss more efficiently then the old Best-Worst method. Traditional BWM struggles to properly combine decision-makers' preferences, which often leads to errors and inaccurate results because it relies on the average operator. This averaging approach assigns equal weight to every decision-maker. In contrast, Bayesian-BWM offers a more effective way to calculate the aggregated criteria weights for multiple decision-makers by considering them from a probabilistic perspecti(Mohammadi & Rezaei, 2020) .Here are the steps that have been performed :

Step 1: The DM (Decision Makers) needs to provide a set of decision criteria $C = \{c_1, c_2, \dots, c_n\}$.

Step 2: The DM selects the best (c_B) and the worst (c_W) criteria from C.

Step 3: The DM conducts the pairwise comparison between the best (c_B) and the other criteria from C.

Here, the DM calibrates his/her choice of the best criteria to other criteria by a number between (1-9). The pairwise comparison leads to the "Best-to-Others" vector A_B as

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$

where a_{Bj} represents the preference of the best (c_B) to the criterion $c_j \in C$.

Step 4 : The DM conducts the pairwise comparison between the worst (c_W) to others criteria from C.

Here again, the DM calibrates his/her choice of the worst criteria to other criteria by a number between (1-9). The result of this step is the "Others-to-Worst" vector A_W as

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$$

where a_{jW} represents the preference of the criterion $c_j \in C$ over the worst (c_W).

Step 5: The optimal weight vector $w^* = (w_1^*, w_2^*, \dots, w_n^*)$ is obtained by minimizing the maximum deviations from the relations $w_B/w_j = a_{Bj}$ and $w_j/w_W = a_{jW}$, subject to non-negativity and the weights summing to one.

$$\min_{w} \max_{j} \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}$$

$$\sum_{j=1}^{n} w_j = 1,$$

$$w_j \geq 0 \quad \forall j = 1,2, \dots, n.$$

Similarly, the weight vector can also be calculated by the following problem.

$$\min_{\xi,w} \xi$$

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi \quad \forall j = 1,2,\dots,n$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi \quad \forall j = 1,2,\dots,n$$

$$\sum_{j=1}^{n} w_j = 1,$$

$$w_j \geq 0 \quad \forall j = 1,2,\dots,n.$$

4. Analysis and Result

This section displays the criteria's established rankings as determined by Bayesian BWM.

4.1 Analysis of the Result

For each cluster, a weighted graph has been plotted.

Figure 1 shows the credal ranking of the three main clusters or criteria. The most significant cluster was Technological Readiness(.3874) ,2nd was Sustainability & Supply Chain (.321) , Followed by Supply chain and Production efficiency (.2916). The technological readiness cluster criteria requires special attention from managers since they are more important than those of the other clusters. However, the Sustainability and supply chain cluster are close to the technological readiness cluster in terms of weight, which suggests that to improve sustainable supply chain with I4.0 practices in the garments industry managers and policymakers must pay attention to both clusters. Furthermore, It was discovered that the Technological Readiness and Supply Chain & Production Efficiency cluster had stronger alignment (0.97 confidence-level) than the Sustainability & Supply Chain cluster (0.77 confidence-level). Furthermore, with a 0.86 confidence-level, the Supply Chain & Production Efficiency cluster showed higher implementation similarity compared to the Sustainability & Supply Chain cluster.

Figure 3 shows the local ranking of the sub-criteria's of Technology readiness cluster. In here the most important sub-criteria is Advanced Analytics and AI (0.2), followed by IoT sensors and RFID (0.155), Blockchain(.01393), Additive Manufacturing (3D Printing) (0.1336), Robotic Sewing Lines(0.1102), Cloud Computing and Big Data Platforms(0.1101), Digital Twin technology (0.0785), Robots or Automatic Guided Vehicles(0.0732). Advanced Analytics and AI showed the highest values among all of the other sub-criteria in Technology Readings. Figure 2 uses colored links to illustrate the network between the sub-criteria drivers in the areas of technology readiness.

Figure 4 shows the local ranking of the sub-criteria of the Supply Chain & Production Efficiency cluster. In this case, the most important sub-criteria is Digital Supply Chain Visibility (0.2154), followed by Automated Quality Control & Defect Detection (0.1993), Lead Time Reduction to Port/Buyer (0.1524), Demand-Driven Production (Lean-Agile Hybrid) (0.1472), Collaborative Supply Chain Management (0.1178), VMI, or Vendor Managed Inventory (0.1153), and CRP / Smart Replenishment (0.0526). Among these, Digital Supply Chain Visibility shows the highest value, highlighting its strong influence compared to the other sub-criteria in the Supply Chain & Production Efficiency cluster. Figure 4 uses colored links to demonstrate the network relationships between the sub-criterion drivers in this cluster.

Figure 5 shows the local ranking of the sub-criteria of the Sustainability and Supply Chain cluster. In this case, the most important sub-criteria is Waste and Emission Reduction (0.2163), followed by Reverse Logistics & Product Take-Back Programs (0.2031), Eco-Friendly Packaging & Logistics (0.1557), Renewable Energy Adoption in Supply Chain (0.1491), Circular Economy & Recycling (0.0947), Sustainable Component Sourcing (0.0775), Green Warehouse Practices (0.0657), and Ethical Labor & Compliance Monitoring (0.0379). Among these, Waste and Emission Reduction shows the highest importance, indicating its significant role compared to other sub-criteria in the Sustainability and Supply Chain cluster. Figure 5 uses colored links to highlight the interconnections among the sub-criteria drivers within this cluster.

In Figure 6 we have shown the global weight of the drivers or criterias .In comparison to all the criterias or drivers Advance analytics and Ai has shown(0.0691434) the highest value . So it is much more influential than all the other criteria. Followed by it the next two most important criterion are Digital Supply Chain visibility (0.0691434) and Automated quality control and Defect Detection (0.0691434). The lowest value has been showed by Ethical Labor & Compliance Monitoring (0.01105164)

So, the best criteria among the clusters for this survey is Technology readiness. In the time of I4.0 there is no option but to adopt the new technologies. Advanced analytics and Ai, IoT sensor ,Blockchain,Big data and Dashboard are the most crutial parts of this generation.

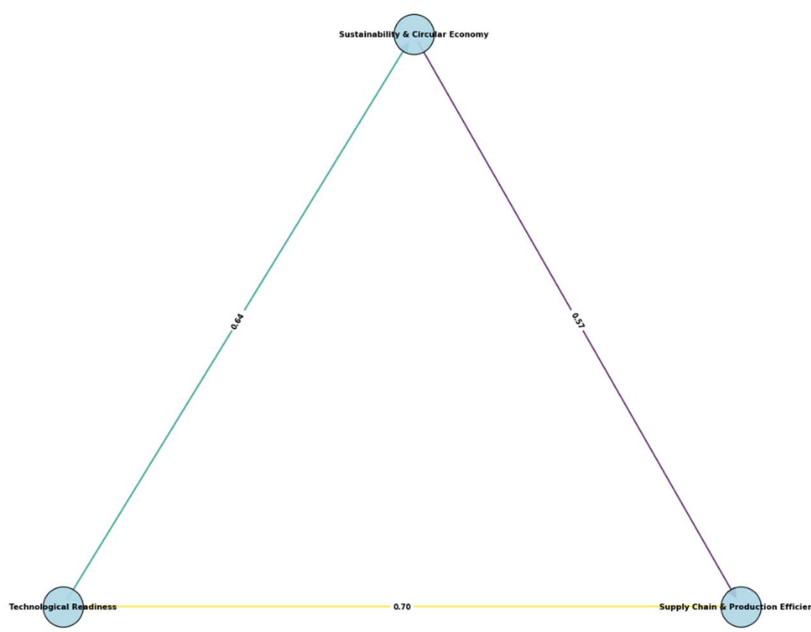

Figure 2: Ranking of the Main drivers

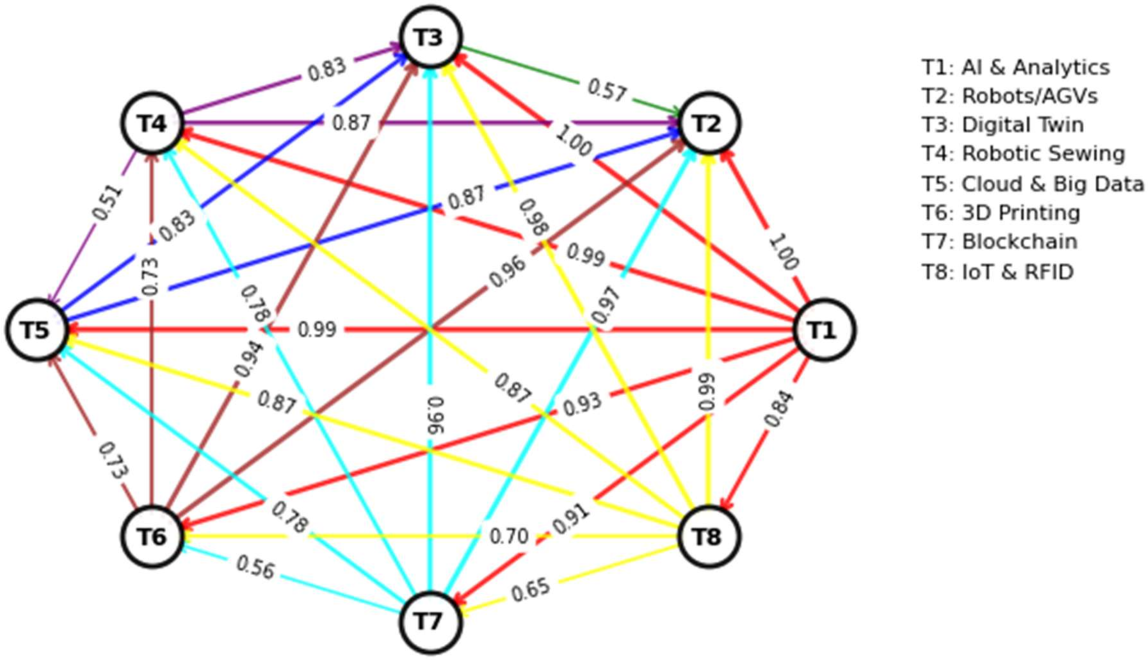

Figure 3: Ranking of the Technology Readiness drivers

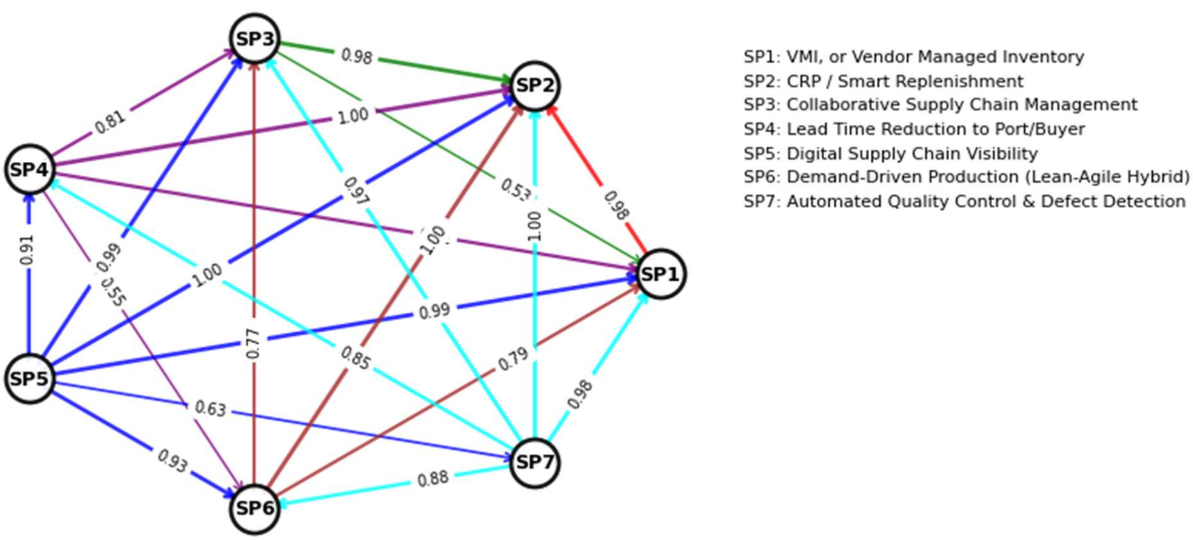

Figure 4: Ranking of the Supply Chain and Production Efficiency

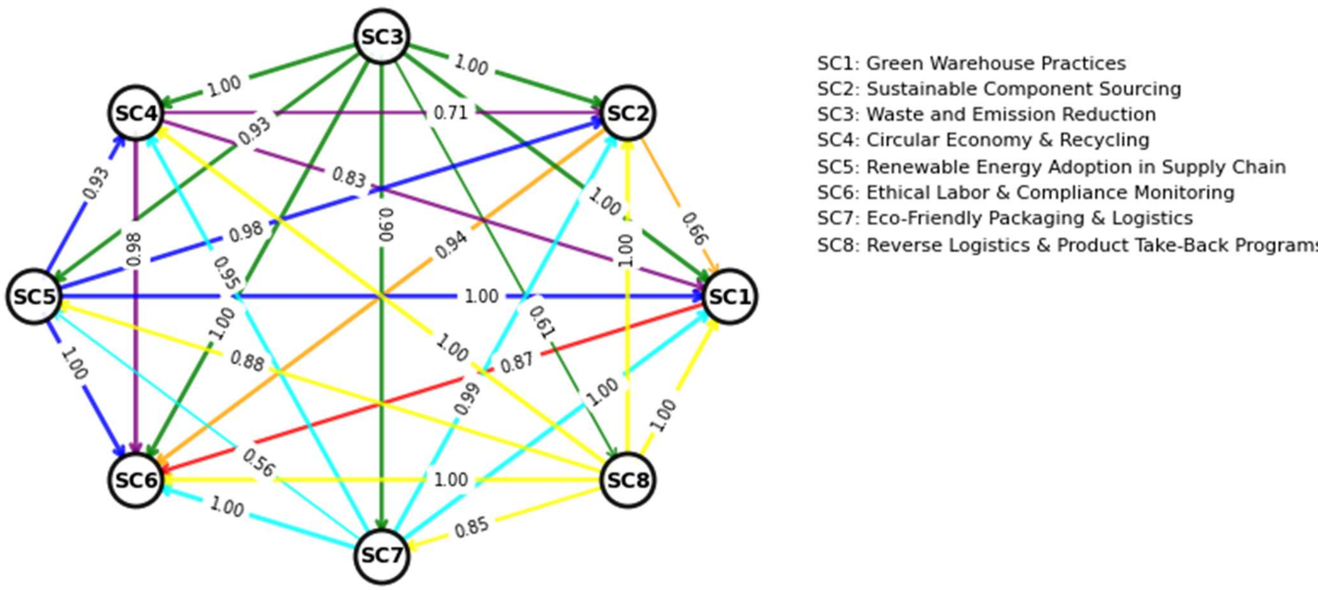

Figure 5: Ranking of the Sustainability and Circular Economy drivers

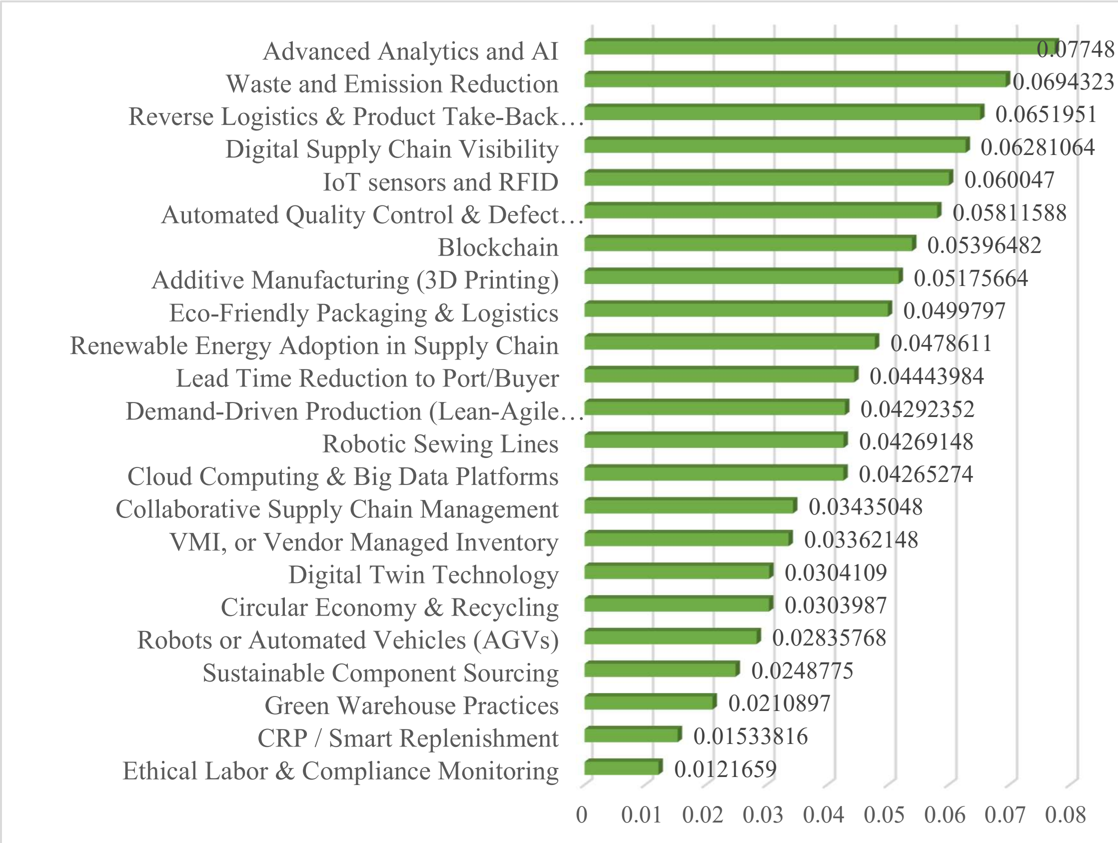

Figure 6: Global Ranking of all the sub-criterion

Check **table 1-3** of the appendix part to see the confusion matrix of the ranking values for the credal ranking

4.2 Outcome validation :

In the conducted study , the criteria's that were identified for implementation of I4.0 in garments for sustainability to improve the overall improvement of the supply chain were thoroughly tested by industry . This research had a three-phase methodology. The 15 Decision Makers all had expert understanding of the topic. The DM's were carefully chosen according to their broad experience, current position in supply chain or higher position in the garments industry and knowledge of digitalization and sustainability .All the participants agreed on the significance and applicability of these factors, confirming that they align with the research findings.The criterion guaranteed the relevance and insightfulness of the comments and reviews. Lastly, the study showed the experts the model that prioritized the drivers according to their significance and influence by utilizing the

The proposed model was critically evaluated by the participants, also confirming the ranking order and offering siggestions to make it more refined the priotization for practical application in garmnets industryThroughout this process, interactions with industry professionals not only validated the findings but also contributed valuable insights. The identified strategies for implementing Industry 4.0 in sustainable supply chains were demonstrated to be both theoretically robust and practically feasible through a comprehensive validation procedure. The study's outcomes provide a pathway for decision-makers in the garments sector to effectively adopt Industry 4.0 technologies within a sustainable framework, fostering a more efficient, resilient, and environmentally responsible supply chain ecosystem.

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5. Key Findings and Their Relevance

5.1 Discussion of the findings

Based on the results in the Bayesian BWM framework developed in this paper, some of the key drivers to adopt the implementation of the Industry 4.0 technology in export garment-oriented supply chains to boost sustainable performance have been identified.

The first significant driver is the "Advanced Analytics and AI (T02)" that contributes by the global weight of 0.0775. This driver emphasizes highly the importance of data-driven decision making capabilities that can be used to make predictive analytics, demand forecasting and product optimization thus establishing the way of intelligent automation and increased operational efficiency. Advanced analytical systems help organizations to maximize resource utilization, gradually improve production performance and leverage machine learning algorithms (Salman et al., 2025b). When addressed intelligently, KPIs can help organizations avoid quality problems and strive toward achieving continuous improvement goals by means of predictive insights and smart data processing. Improved Precision of Monitoring and Control (SP08) with weight of 0.0633 comes in third place, which is the ability to monitor precision and control, which prevent defects in real-time and contribute to smart manufacturing sustainability (Govindan et al., 2015b). Proper deployment is a key success factor in competitive advantage and successful implementation of Industry 4.0 yet previous studies reveal that inability to monitor quality in real-time deters adoption in garment industries. The third key driver is Digital Supply Chain Visibility (SP05) with a weight of 0.0634 that promises transparency, responsiveness, and sustainable practices by being visibly apparent, minimizing waste and embedding the circular economy (Genovese et al., 2017). The "IoT sensors and RFID (T08)" driver is the fourth most significant with a global weight of 0.0600, facilitating real-time connectivity and data collection throughout manufacturing operations to enable seamless information flow and automated tracking systems (Salman et al., 2025a). "Blockchain (T07)" represents the fifth driver with a global weight of 0.0540, providing secure and transparent transaction recording capabilities that enhance supply chain traceability and build trust among stakeholders through immutable data verification (Singh et al., 2025b). The "Additive Manufacturing/3D Printing (T06)" driver holds the sixth position with a global weight of 0.0518, enabling rapid prototyping, customized production, and reduced material waste through layer-by-layer manufacturing processes (Lahdhiri et al., 2022). "Eco-Friendly Packaging & Logistics (SC07)" is the seventh driver with a global weight of 0.0500, promoting sustainable packaging solutions and green transportation methods that minimize environmental impact throughout the supply chain (Mim et al., 2024c). The "Renewable Energy Adoption in Supply Chain (SC05)" driver ranks eighth with a global weight of 0.0479, supporting the integration of clean energy sources to reduce carbon footprint and enhance environmental sustainability. "Lead Time Reduction to Port/Buyer (SP03)" occupies the ninth position with a global weight of 0.0445, focusing on streamlining delivery processes and optimizing logistics to meet tight deadlines and enhance customer satisfaction. The "Demand-Driven Production/Lean-Agile Hybrid (SP06)" driver is tenth with a global weight of 0.0429, combining lean manufacturing principles with agile responsiveness to market demands for optimal production efficiency. "Robotic Sewing Lines (T04)" represents the eleventh driver with a global weight of 0.0427, automating complex sewing operations to improve precision, consistency, and productivity in garment manufacturing (Lahdhiri et al., 2022). The twelfth position is by the driver-learning Milton Keynes (T05) with a global value of 0.0426, which delivers scalable computing resources and high-order data analytics in order to make informed decisions. The thirteenth driver is called

Collaborative Supply Chain Management (SP02) having a global weight of 0.0345, and it cooperates and orchestrates amongst the suppliers, owners, and buyers to ensure the optimum supply chain performance. The "VMI or Vendor Managed Inventory (SP01)" driver is ranked at position 14 with a global weight of 0.0336 whereby the suppliers are capable of managing the inventory levels on the customers premises, to help minimize stock outs and maximize inventory expenses. Taking the fifteenth position with a global weight of 0.0304 is the digital twin technology (T03) in the form of the bringing into existence of virtual replicas of physical systems in order to allow simulation, monitoring, and optimization of manufacturing processes (Debnath et al., 2023a). The "Circular Economy & Recycling (SC04)" driver is ranked 16th with an overall weight of 0.0304, which encourages the reduction of wastes, reuse of materials, closed-loop-type production systems to support Sustainable operation. Automated Vehicles/AGVs/Robots/T01 are the seventeenth driver having a universal weight of 0.0284 which will automate movement and handling of materials in manufacturing plants. The driver under the thirteenth position, the sustainable component sourcing (SC02), has global weight 0.0249, which guarantees environment-friendly component sourcing and supplier selection criteria. The nineteenth driver is titled down to earth practices and is referred to as Green Warehouse Practices (SC01), which has a global weight of 0.0210, to realize energy efficient storage solutions and environmentally responsible warehouse practices. The "CRP/Smart Replenishment (SP04)" driver ranks twentieth with a global weight of 0.0154, utilizing intelligent algorithms for automated inventory replenishment and demand planning. Finally, "Ethical Labor & Compliance Monitoring (SC06)" occupies the final position with a global weight of 0.0122, ensuring adherence to labor standards, worker rights, and ethical manufacturing practices throughout the supply chain (Munim et al., 2022).

5.2 Theoretical Implications

The findings of this research enrich theoretical understanding of how Industry 4.0 adoption unfolds in the context of export-oriented garment supply chains, particularly in developing economies. By prioritizing the critical adoption criteria through Bayesian BWM, the study demonstrates how technological readiness, supply chain efficiency, and sustainability collectively shape digital transformation outcomes. This approach highlights that 4.0 adoption is not a purely technological issue but an integrated socio-technical phenomenon where technological, organizational, and environmental factors converge.

The study reinforces the notion that technological readiness is a precursor to digital integration, underscoring the significance of infrastructure, automation capability, and data-driven decision-making frameworks before supply chain-wide efficiency and sustainability gains can be realized. This aligns with broader theories of staged digital maturity, where firms must first establish a foundational digital base before advancing toward more complex sustainability-driven practices.

Furthermore, the findings extend theoretical discourse by demonstrating that sustainability and efficiency are not competing but complementary priorities within Industry 4.0 adoption. The Bayesian BWM framework illustrates that waste and emission reduction, real-time digital visibility, and automation can be synergistically leveraged to improve competitiveness while simultaneously aligning with sustainable development goals (SDGs).

From a methodological perspective, the integration of Bayesian BWM into the analysis of adoption criteria advances theoretical insights into multi-criteria decision-making under uncertainty. This reinforces the applicability of probabilistic weighting models for capturing heterogeneous expert judgments in contexts where decision-making involves high uncertainty and resource constraints.

The study also opens new avenues for theorizing about digital transformation pathways in developing economies. Unlike models derived from advanced economies, the findings indicate that infrastructural and financial readiness strongly mediate adoption, requiring localized frameworks rather than one-size-fits-all approaches.

In summary, this research contributes to the theoretical literature on Industry 4.0 by:

1. Establishing technological readiness as a foundational driver for successful 4.0 implementation in garment supply chains.
2. Demonstrating the interdependence of supply chain efficiency and sustainability in digital transformation.
3. Extending the use of Bayesian BWM as a robust theoretical tool for prioritizing adoption criteria under uncertainty.
4. Offering a context-specific theoretical model for Industry 4.0 adoption in developing economies, highlighting the role of infrastructural and skill readiness.

5.3 Managerial and Policy Implications

For managers, consultants, and industry practitioners striving to implement Industry 4.0 technologies within the export-oriented garment supply chain, the findings of this study provide significant insights. Managers can prioritize their digital transformation strategies and formulate effective action plans by aligning them with the study's identified key drivers. For instance, digital supply chain visibility and automated quality control must be prioritized to ensure efficiency and competitiveness, while investments in advanced analytics, AI, and IoT systems can provide the foundation for real-time decision-making. Management involvement and leadership commitment remain indispensable, as the transition to Industry 4.0 requires both technological and cultural adaptation. In addition, structured training and upskilling programs for employees can enhance their capacity to leverage digital tools, thus supporting organizational readiness and ensuring the sustainability of the transformation process. By mapping their strategies to the prioritized drivers, managers can build resilient and future-ready garment supply chains.

The study also yields important implications for policymakers. Regulations and policies should be designed to encourage the development of digital infrastructure, workforce skill enhancement, and sustainable manufacturing practices within the garment industry. For example, policy incentives in the form of tax benefits, subsidies, or financial support for Industry 4.0 technology adoption can reduce the burden of high initial investment costs for manufacturers. Furthermore, governments should promote collaborative platforms and knowledge-sharing hubs where firms, technology providers, and academia can co-develop solutions tailored to local industry needs. By fostering digital literacy and emphasizing compliance with international sustainability standards, policymakers can enhance the global competitiveness of the RMG sector. In doing so, they contribute to the achievement of national economic growth objectives while supporting global sustainability agendas such as the SDGs.

In conclusion, this study offers valuable guidance for managers, consultants, and policymakers alike. By recognizing and acting upon the prioritized drivers, managers can improve supply chain performance, reduce inefficiencies, and enhance sustainability outcomes. Policymakers, meanwhile, can accelerate the adoption of Industry 4.0 in garment supply chains through supportive frameworks, infrastructure development, and skill-building initiatives. Collectively, these efforts can lead to greater competitiveness, enhanced resilience, and stronger alignment with the demands of an increasingly digital and sustainability-driven global market.

6. Conclusion & Future Studies

Bangladesh garment industry is in the top of the chain but has recently fallen behind the race due to slow adoption of I4.0 technologies and for not focusing on sustainability. But it is gradually bulding momentum as eveyone is looking to improve quality and efficency. Despite this trend research focusing on the garments sector in emerging economies remains limited. particularly regarding the prioritization of critical drivers that enable such integration. This study addressed this gap by applying the Bayesian Best-Worst Method (Bayesian BWM) to identify, categorize, and rank the most significant drivers of sustainable supply chain adoption in the garments industry.

he analysis for the study started with a wide review of the literature to identify possible drivers and that were later validated with experts' opinions. The drivers were then clustered into three groups: 1) technological readiness; 2) orientation to organisatoric and economic conditions; and 3) sustainable practices. To derive weights that are aggregated relative to importance and confidence rating given by the experts, the Bayes BWM method was pursued. In the study, technological readiness, management commitment, and green supply chain initiatives together form the three critical drivers for the successful adoption. These drivers, together, compose an effective frame of reference that is needed to link the technology to leadership involvement and sustainability, where they will be leveraged to obtain sustainable competitive advantage.

The article truly presents systematic frameworks of drivers from the existing literature: however, it is pertinent to acknowledge limitations in the presented research. The data was collected in a particular sector and geographic context, which may limit drawing a general conclusion from the study. Additionally, the Bayesian BWM generated more robust insights into the prioritisation of drivers, but not all potential drivers could be captured, and additional dimensions (factors) were potentially outside the scope of this work. Future studies can expand this work by studying other emerging sectors and integrating hybrid methods (such as fuzzy TISM or ISM) or further MCDM techniques (like fuzzy TOPSIS and VIKOR) to corroborate and contrast findings. Furthermore, more general application of the framework with greater insights into sustainable supply chain strategies would derive from broader studies both deep into industries and national or geographic contexts.

In conclusion, this study added to the growing literature on sustainable supply chain management in the garments industry in emerging economies. The application of the Bayesian BWM approach provides a new methodological approach for identifying and then prioritising major drivers, ultimately to help policy actors, practitioners, and industry leaders make informed decisions. The results of this study highlighted strong managerial engagement, technology readiness, and sustainability-related practices as key enabling factors to developing sustainable and resilient supply chains.

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Appendix

Table 1: Estimated Correlation Matrix for Clusters

Cluster	Technological Readiness (0.3874)	Supply Chain & Production Efficiency (0.2916)	Sustainability & Supply Chain (0.3210)
Technological Readiness (0.3874)	0	0.7	0.64
Supply Chain & Production Efficiency (0.2916)	0.3	0	0.43
Sustainability & Supply Chain (0.3210)	0.36	0.57	0

Table 2: Estimated Correlation Matrix for Clusters

Technological Readiness (0.3874)	T1 (0.07)	T2 (0.20)	T3 (0.08)	T4 (0.11)	T5 (0.11)	T6 (0.13)	T7 (0.14)	T8 (0.16)
T1(0.07)	0	0	0.43	0.13	0.13	0.04	0.03	0.01
T2 (0.20)	1	0	1	0.99	0.99	0.93	0.91	0.84
T3 (0.08)	0.57	0	0	0.17	0.17	0.06	0.04	0.02
T4 (0.11)	0.87	0.01	0.83	0	0.51	0.27	0.22	0.13
T5 (0.11)	0.87	0.01	0.83	0.49	0	0.27	0.22	0.13
T6 (0.13)	0.96	0.07	0.94	0.73	0.73	0	0.44	0.3
T7 (0.14)	0.97	0.09	0.96	0.78	0.78	0.56	0	0.35
T8(0.16)	0.99	0.16	0.98	0.87	0.87	0.7	0.65	0

Table 3: Estimated Correlation Matrix for Clusters

Sustainability & Circular Economy (0.3210)	SC1 (0.07)	SC2 (0.08)	SC3 (0.22)	SC4 (0.09)	SC5 (0.15)	SC6 (0.04)	SC7 (0.16)	SP8 (0.20)
SC1 (0.07)	0	0.34	0	0.17	0	0.87	0	0
SC2 (0.08)	0.66	0	0	0.29	0.02	0.94	0.01	0
SC3 (0.22)	1	1	0	1	0.93	1	0.9	0.61
SC4 (0.09)	0.83	0.71	0	0	0.07	0.98	0.05	0
SC5 (0.15)	1	0.98	0.07	0.93	0	1	0.56	0.12
SC6 (0.04)	0.13	0.06	0	0.02	0	0	0	0
SC7 (0.16)	1	0.99	0.1	0.95	0.44	1	0	0.2
SP8 (0.20)	1	1	0.39	1	0.88	1	0.8	0

Table 4: Estimated Correlation Matrix for Clusters

Supply Chain & Production Efficiency (0.2916)	SP1 (0.12)	SP2 (0.12)	SP3 (0.15)	SP4 (0.05)	SP5 (0.22)	SP6 (0.15)	SP7 (0.20)
SP1 (0.12)	0	0.47	0.18	0.98	0.01	0.21	0.02
SP2 (0.12)	0.53	0	0.19	0.98	0.01	0.23	0.03
SP3 (0.15)	0.82	0.81	0	1	0.09	0.45	0.15
SP4 (0.05)	0.02	0.02	0	0	0	0	0
SP5 (0.22)	0.99	0.99	0.91	1	0	0.93	0.63
SP6 (0.15)	0.79	0.77	0	1	0.07	0	0.88
SP7 (0.20)	0.98	0.97	0.85	1	0.37	0.88	0

Table 5: Participants summary

	Experience	Designation	Number of experts	Percentage
For determining and clustering the key drivers for applying Industry 4.0 in garment supply chains				
Total experts N = 12	More than 16 years	Executive Director	2	16.67
		General Manager	2	16.67
		Assistant General Manager	1	8.33
		Manager	1	8.33
	10–16 years	General Manager	2	16.67
		Assistant General Manager	2	16.67
		Manager	1	8.33
	7–10 years	Academic (Professor)	1	8.33
For determining the ranking of key drivers using Bayesian BWM				
Total experts M = 13	More than 16 years	Executive Director	2	15.38
		General Manager	2	15.38
		Assistant General Manager	1	7.69
		Manager	1	7.69
	10–16 years	General Manager	2	15.38
		Assistant General Manager	2	15.38
		Manager	1	7.69
	7–10 years	Academic (Professor)	2	15.38
Total			25	100%