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Integrating Digital Product Passport for Optimal Supplier and Reverse-Logistics Hub Co-Selection in Bangladesh's Circular Textiles Supply Chain

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Abstract

This research formulates and validates a novel hybrid Multi-Criteria Decision-Making (MCDM) model to address the combined decision challenge of the optimal choice of suppliers and reverse-logistics centers needed to achieve digital-enabled circularity in the Bangladesh textiles industry. The study measures 12 metrics under three strategic pillars: Digital Product Passport (DPP) Readiness, the Social-Circular Index (SCCI) and Hub Feasibility. The framework uses the Best-Worst Method (BWM) of weighting criteria and Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) of dual ranking based on the data gathered at five factories and two logistical hubs. Findings show that the DPP Fields Available (D1 = 0.6207) and Water Reuse (C1 = 0.5063) are the most significant in selecting suppliers, whereas the decision on the hub belongs to Cost per Returned Unit (H1 = 0.6126). The TOPSIS ranking indicates Supplier F3 and Gazipur Hub (H_GZ) to be the best pairing. Importantly, the initial Veto Rule guarantees social compliance, whereas a sensitivity analysis testifies to the stability of the final selection. The model provides a measurable platform to brands that aim to introduce digital traceability and efficiency in their operations to adapt to the new global circular requirements.

Keywords
Digital Product Passport (DPP), Social-Circular Index (SCCI), Reverse Logistics Hub, Circular Economy (CE).

1. Introduction
As worldwide supply chains move toward circular economy models that aim to decrease waste, increase material recirculation, and prolong product lifecycles, the textile and clothing industry is going through a fundamental transformation. The fast digitization of supply-chain activities and the increasing environmental imperatives are the primary forces behind this change. Digital systems and traceability technologies are being used more and more by brands to track product lifecycles, manage compliance, and implement circularity efforts (Orisadare et al., 2025). The DPP is a structured data carrier that has played an important role in enhancing transparency and circular textile flows within this environment. It contains product-level data about materials, chemicals, environment effects, and social conformity. The shift toward digital product level visibility in the textile business has been inconsistent even though international legislations such as the upcoming DPP bill in the EU have accelerated the discussion on traceability (Vivian, 2025).

As the world's number two garment exporter, Bangladesh is well-entrenched in the new sustainability standards. With the green building certifications, remediation efforts, and energy-efficient renovations, the country has materialized as a sourcing destination of global brands in the last ten years (Akhter et al., 2019). At the same time, the increasing interest in circularity is raising new requirements. Brands are now expected to participate in reverse logistics systems allowing clothes to be taken back, repaired, and reprocessed, and have verified information about chemical inputs, manufacturing processes, and fiber composition (Sandin & Peters, 2018). These are critical components of achieving circular material flows in textile value chains. However, despite advancements in sustainability practices, Bangladesh’s textile sector still faces gaps that hinder its readiness for DPP-driven circularity. Data at the product level is inconsistent due to the disjointed nature of digital traceability systems. Social sustainability performance, which involves factors such as working hours, wage justice and the safety at the work place, vary widely across the factories (Azizul Islam & Deegan, 2008). Moreover, the reverse logistics infrastructure is also in its initial development phase, and existing hubs vary significantly in terms of governance, cost structures, turnaround times, and emissions (Govindan et al., 2013). These limitations lead to the fact that it is imperative to adopt integrated assessment techniques that are not based on the application of individual performance indices but can measure hubs and suppliers as a unit.

Cleaner production, more environmentally friendly factories, and better compliance procedures are driving progress in Bangladesh's textile sector. Nevertheless, rather than cohesive systems, multiple frameworks are employed to meet the requirements of circularity, e.g., traceability, social protection, and reverse-logistics preparedness. Given that circular return schemes require extensive and proven product information, this complicates the process of the brands and manufacturers determining which suppliers are eligible to join. Digital traceability is not fully complete and is still not evenly distributed as an important requirement of DPP systems. Many factories rely on a mix of spreadsheets, paper logs, and partially integrated ERP modules, resulting in incomplete data on fiber composition, dyeing chemicals, and processing conditions (Matias et al., 2025). Such fragmentation makes it difficult to generate DPP-ready product files, potentially limiting market access for Bangladesh as regulations tighten. Social sustainability presents similar inconsistencies. Although substantial improvements have been made since major industrial reforms, persistent issues such as wage levels, excessive overtime, and worker representation continue to shape global perceptions of the sector (Anisul Huq et al., 2014). Social compliance indicators are rarely embedded within digital traceability or environmental reporting frameworks, creating siloed data systems that are misaligned with global expectations for integrated sustainability reporting (Akhter et al., 2019). Another area that is not uniform is reverse logistics capacity, which is crucial for circular returns. The prices of transportation, reprocessing capacity, emissions, and adherence to labor standards are significantly different between industrial belts and hubs such as Gazipur and Chattogram. These variances cause uncertainty in brands that prepare the circular return channels. Most of the studies based on circularity have failed to research the logistics and social protection, with most of the studies being purely material- and environment-related (Freeman & Chen, 2015). Suppliers and hubs cannot be systematically assessed according to DPP preparedness, social-circular performance, and operational feasibility because no such integrated model exists.

1.1 Research Objectives
The specific objectives of this research are:

1) To build and implement a hybrid BWM-TOPSIS decision framework incorporating DPP readiness, social-circular performance and reverse-logistics feasibility to create a tri-dimensional evaluation model.
2) To apply the integrated framework using real-world data to rank manufacturers and hubs and identify the single optimal supplier-hub pairing for circular textile return operations.
3) To verify the stability of the final ranking through sensitivity analysis and provide actionable, validated insights for stakeholders preparing to meet DPP and circular economy requirements.

2. Literature Review

There is a growing need for more product traceability, material transparency, and environmental responsibility in many industries, but notably the textile industry, as a result of the worldwide trend toward circular economy practices. A key tool for connecting product-level data with sustainable supply-chain decision making has been the Digital Product Passport (DPP), which is part of this larger shift. By incorporating social and environmental indicators throughout the textile lifecycle, Panza et al., (2023) expanded the reach of DPPs and showed how enhanced product data may put circular strategies into action. Following this concept, Zhang & Seuring, (2024) analyzed more than 80 applications of DPPs and demonstrated that DPPs enhance the material traceability and supply-chain transparency, as well as data-driven resource cycles. Nonetheless, industrial readiness is not even. The need to have scalable interoperable models in the developing manufacturing economies such as Bangladesh is emphasized by the fact that according to the findings of Ojansuu, (2024), although DPPs are considered a competitive edge by enterprises, a significant number of them, especially SMEs, face financial and technical challenges.

In the analysis of business-to-consumer (B2C) reverse logistics, Uddin, (2025) stressed the importance of trusting customers and offering incentives for their involvement in addition to physical infrastructure for a successful return. Digital transparency can enhance the efficiency of sorting and recycling in the textile-to-textile network, with research findings by Sandvik & Stubbs, (2019) about textile-to-textile textile recycling networks in Scandinavia indicating that the digital transparency would help eliminate barriers to the process, including complex supply chains and insufficient technology. Besides, Saccani et al., (2023) argued that the structural impediments could be surmounted through textile districts through coordinated orchestration of supply-chain. In addition, Oliveira Silva & Morais, (2022) demonstrated that badly planned outsourcing decisions can obstruct circular objectives, and Jäämaa & Kaipia, (2022) offered predictive first-mile collection models to deal with the problems of end-of-life textile recovery in the face of new regulatory demands.

Research in a different area focuses on sustainability-oriented supplier evaluation, which prioritizes systematic decision-making processes that take economic, social, and environmental factors into account. In their presentation of a hybrid fuzzy AHP-TOPSIS technique to grade yarn suppliers, Alexander & Thomas, (2025) found that labor practices, energy efficiency, and waste minimization are major predictors of sustainable sourcing. Beyond this, Sithi et al., (2025) developed a supplier evaluation model grounded in the Triple Bottom Line philosophy by merging SWARA and TOPSIS. These principles emphasize more on the safety of chemicals, management of the environment and the well-being of workers. Salman et al., (2025) provided further insight into the issues that the RMG industry struggles to manage in the context of the circular economy and enumerated the lack of resources, the absence of teamwork, and ignorance of the ecological issues as the key challenges. In their attempt to illustrate the ways through which transparency in real time can benefit conscientious buyers and consumers, Alves et al., (2024) came up with a tracking platform that utilizes blockchain, and thus able to identify social, economic, and environmental consequences to score them. Although the interest in recycling is high, Dang, (2023) discovered that recyclable textiles find their way to the landfills because of institutional challenges in collection and business participation. Siderius & Poldner, (2021) sounded the alert on systems-level warning that circular interventions could rebound unless they are implemented as a part of a holistic sustainability system.

Research peculiar to the Bangladesh environment highlights its complexity. Although the textile and RMG industry has improved following the major industrial transformations, Islam, (2025) established that the industry has sustainability challenges, including; poor working conditions, poor environmental management, and low economic resilience. Collectively, the findings above indicate a bright future of the circular return systems of the textile industry in Bangladesh through the intermingling of the elements of DPP-enabled transparency and the scoring of the social-circular performances of the suppliers and collection hubs. This would help bring local operations in line with global sustainability expectations.

3. Methodology

The methodology employed in this study is a sequential hybrid MCDM approach, designed to rigorously quantify the performance of circular-enabling suppliers and reverse-logistics hubs as shown in Figure 1. This framework integrates the BWM for precise and consistent criteria weighting, followed by TOPSIS for ranking alternatives based on their distance from ideal performance. The overall process begins with the problem structuring and application of non-negotiable Veto Rules, proceeds through the BWM weighting and dual TOPSIS evaluation and concludes with a sensitivity analysis to confirm the robustness of the optimal supplier-hub pairing.

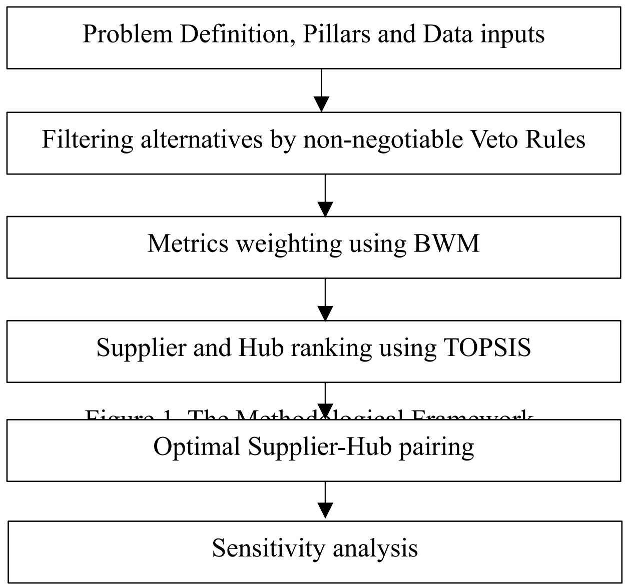

Figure 1. The Methodological Framework

3.1 Problem Definition, Pillars and Data Inputs

The foundation of the decision model involves structuring the problem domain, defining the key evaluation pillars, operationalizing the metrics, and compiling the raw performance data for the alternatives. This approach is necessary due to the simultaneous requirement to evaluate both the manufacturing partner and the enabling logistics infrastructure (Ahmed et al., 2022).

3.1.1 Alternatives, Pillars and Metric Operationalization

The decision problem encompasses the evaluation of five candidate textile suppliers (F1 to F5) and two reverse-logistics hub alternatives (H_GZ for Gazipur and H_CT for Chattogram). To ensure comprehensive assessment of the novel circularity requirements, the overall decision problem is structured around three distinct yet interrelated pillars, encompassing 12 individual sub-criteria. These metrics operationalize key aspects of the circular supply chain, ranging from digital traceability (DPP) to social welfare and physical reverse-flow feasibility. The definition and directionality (Benefit or Cost) of these metrics are detailed in Table 1, which serves as the blueprint for both the BWM and TOPSIS analyses.

Table 1. Pillar Metrics and directions

Pillar	Code	Metric Definition	Unit	Direction	Source
DPP Readiness	D1	% mandatory DPP fields available	%	Benefit (B)	(Carvalho et al., 2025)
	D2	Average data latency to provide full docs	Days	Cost (C)	
	D3	Proof quality (0: None / 1: Internal / 2: Third-party)	Ordinal (0-2)	Benefit (B)	
Social-Circular Index (SCCI)	S1	Overtime hours per worker per month	Hrs/Month	Cost (C)	(Tavana et al., 2021)
	S2	Living-wage gap % (vs. public benchmark)	%	Cost (C)	
	C1	% water reuse in manufacturing	%	Benefit (B)	
	C2	GHG $kgCO_2e$ per kg fabric	$kgCO_2e/kg$	Cost (C)	
	C3	Take-back/repair agreement formally exists	Binary (0/1)	Benefit (B)	
Reverse-Logistics Hub Feasibility	H1	Cost per returned unit (transport + repair)	USD/unit	Cost (C)	(Govindan et al., 2019)
	H2	Turnaround time (days to process return)	Days	Cost (C)	
	H3	Emissions per unit (transport only)	$kgCO_2e$	Cost (C)	
	H4	Basic social safeguards at hub site	Binary (0/1)	Benefit (B)	

3.1.2 Raw Performance Data and Veto Rules

Raw data were collected through targeted surveys with factory managers, analysis of one month of utility and operational logs and cross-referencing public wage benchmarks for the Bangladeshi garment sector. This primary data forms the initial decision matrix for the evaluation process (Table 2 and Table 3).

Table 2. Raw Performance Data for Supplier Alternatives

Alternative	**D1 (%) (B)**	**D2 (days) (C)**	**D3 (0-2) (B)**	**S1 (hrs/m) (C)**	**S2 (%) (C)**	**C1 (%) (B)**	**C2 (kgCO2e/ kg) (C)**	**C3 (0/1) (B)**
F1	85	5	2	8	10	70	0.5	1
F2	70	10	1	15	25	40	0.8	0
F3	95	3	2	5	5	90	0.4	1
F4	65	15	0	20	30	30	1.0	0
F5	80	7	1	10	15	60	0.6	1

Table 3. Raw Performance Data for Reverse-Logistics Hubs

Alternative	H1 (USD/unit) (C)	H2 (days) (C)	H3 (kgCO2e) (C)	H4 (0/1) (B)
H_GZ	1.50	5	0.10	1
H_CT	2.20	7	0.05	1

Crucially, prior to metric weighting, non-negotiable Veto Rules were applied to filter out non-compliant alternatives, ensuring a minimum ethical and digital threshold:

1. **Social Veto:** A supplier is ineligible if the Living-wage gap S2 > 25% or if Overtime hours S1 exceed the legal cap of 48 hrs/month.
2. **DPP Veto:** A supplier is ineligible if DPP Field Availability D1 < 70%.
3. **Hub Veto:** If social safeguard is not found; H4=0, hub excluded.

Application of these rules resulted in the immediate elimination of Supplier F4, which failed both the DPP Veto (65% < 70%) and the Social Veto (30% > 25%), leaving four eligible suppliers (F1, F2, F3, F5) for the subsequent BWM-TOPSIS ranking. No hub alternatives were eliminated, as both scored H4=1.

3.2 Metrics Weighting using BWM

The complexity and subjective nature of evaluating criteria across technological (DPP readiness), social and circular pillars necessitate a robust weighting methodology. The BWM was selected over alternative methods, such as the Analytic Hierarchy Process (AHP), due to its reduced need for pairwise comparisons (2n-3 instead of n(n-1)/2), which leads to higher consistency and more reliable results (Rezaei, 2015). The criteria weighting was conducted by a senior operations manager in the textile supply chain to ensure industry expertise.

3.2.1 BWM Model Implementation and Weight Derivation

The BWM procedure involves five core steps to derive the optimal weight vector, $u = (u_1, u_2, ..., u_n)$, for each criterion $j \in \{1, 2, \ldots, n\}$ within a pillar, where u_j represents the relative importance of criterion j.

A. Comparison Vectors

1. **Identify Optimum and Minimum Criteria:** The decision-maker identifies the Optimum Criterion "O" (most important) and the Minimum Criterion "M" (least important) for each pillar.
2. **Optimum-to-Other Vector (D_O):** The decision-maker compares the Optimum criterion (O) against all other criteria (j) using a 1-9 scale, forming the vector $D_O = (d_{O1}, d_{O2}, \ldots, d_{On})$.
3. **Other-to-Minimum Vector (D_M):** The decision-maker compares all other criteria (j) against the Minimum criterion (M) using the same 1-9 scale, forming the vector $D_M = (d_{1M}, d_{2M}, \ldots, d_{nM})^T$.
4.

B. Optimization and Weight Calculation

The optimal weights (u^*, ε^*) are found by solving the following minimax mathematical model, which minimizes the maximum absolute differences between the computed weight ratios and the stated preference ratios, subject to the constraints that the weights must sum to unity.

$$\min \varepsilon^L$$
$$\text{s.t.}$$
$$\left|\frac{u_O}{u_j} - d_{Oj}\right| \leq \varepsilon_L, \text{ for all j}$$
$$\left|\frac{u_j}{u_M} - d_{jM}\right| \leq \varepsilon_L, \text{ for all j}$$
$$\sum_{j=1}^{n} u_j = 1$$
$$u_j \geq 0, \text{ for all j}$$

In the model above, ε^L is the indicator of consistency in the comparisons. The linear programming model is solved to obtain the final optimal weights u_j*. The consistency of the results is assessed using the Consistency Ratio (CR), which compares the calculated ε^{L} to a consistency index (CI) derived from the BWM's maximum possible ε^{L} for the given scale (Liang, 2021; Rezaei, 2015). All pillars demonstrated an acceptable CR, validating the preference inputs.

C. Final BWM Weights

The optimal weights derived from the BWM process for all three pillars are presented in Table 4. These weights (u_j*) will be used as the priority vector (w) for the subsequent TOPSIS ranking.

Table 4. Optimal Criteria Weights Derived by BWM

Code	Optimal Weight (u_j*)	Code	Optimal Weight (u_j*)
D1	0.6207	C2	0.1496
D2	0.2759	C3	0.0855
D3	0.1034	H1	0.6126
S1	0.0592	H2	0.1802
S2	0.1995	H3	0.0631
C1	0.5063	H4	0.1441

3.3 Supplier and Hub Ranking using TOPSIS

The final phase employs TOPSIS to rank the eligible supplier and hub alternatives. TOPSIS is a powerful compensatory method that evaluates alternatives based on their geometric distance from an ideal scenario: the choice should be closest to the Positive Benchmark (Ideal) and furthest from the Negative Benchmark (Anti-Ideal) (Tzeng & Huang, 2011).

The process is executed in three sub-steps, applied separately to the set of eligible suppliers (F1, F2, F3, F5) and the two hub alternatives (H_GZ, H_CT), using the BWM weight vector u_j* (Table 4) as the criteria priorities (w).

3.3.1 Data Normalization and Weighted Matrix Construction

The raw performance matrix X is transformed into the Weighted Normalized Matrix (V).

1. **Normalization:** The raw data (x_{ij}) must first be converted into a comparable scale (0 to 1) using the Min-Max normalization technique as shown in Eq. (1). This accounts for the mixed directionality (Benefit/Cost) of the 12 metrics (Zimmermann, 2011).

$$Normalized\ value\ (z_{ij}) = \begin{cases} \dfrac{x_{ij} - min_i x_{ij}}{max_i x_{ij} - min_i x_{ij}} & ; for\ Benefit\ criteria \\ \dfrac{max_i x_{ij} - x_{ij}}{max_i x_{ij} - min_i x_{ij}} & ; for\ Cost\ criteria \end{cases} \quad (1)$$

2. **Weighted Normalization:** The normalized matrix (Z) is multiplied by the BWM priority vector (w) to construct the Weighted Normalized Matrix (V) as shown in Eq. (2), where v_{ij} represents the weighted score of alternative i on criterion j.

$$v_{ij} = w_j \times z_{ij} \quad (2)$$

3.3.2 Ideal Solution Determination

The TOPSIS method identifies the Positive Benchmark (PB) and the Negative Benchmark (NB) using the extreme values from the weighted matrix (V).

1. Positive Benchmark (A^+): The maximum weighted score for each criterion, representing the ideal performance achievable as shown in Eq. (3):

$$A^+ = \left\{ v_j^+ \middle| v_j^+ = \max v_{ij}, j = 1,2,\dots,n \right\} \quad (3)$$

2. Negative Benchmark (A^-): The minimum weighted score for each criterion, representing the worst performance within the dataset as shown in Eq. (4):

$$A^- = \left\{ v_j^- \middle| v_j^- = \min v_{ij}, j = 1,2,\dots,n \right\} \quad (4)$$

3.3.3 Final Ranking and Optimal Selection

The final ranking is determined by calculating the Euclidean distances from each alternative to the PB and NB.

1. **Separation Distance Calculation:** The separation distances from the Positive Benchmark (G^+) and the Negative Benchmark (G^-) are calculated for each alternative i as shown in Eq. (5) and (6):

$$G_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \qquad (5)$$

$$G_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \qquad (6)$$

2. **Relative Closeness Coefficient (R_i):** The final Relative Closeness Coefficient R_i is computed as shown in Eq. (7), indicating how close an alternative is to the PB relative to the distance from the NB (Ren et al., 2017; Tzeng & Huang, 2011). The alternatives are ranked in descending order of R_i, where the maximum value signifies the optimal selection.

$$R_i = \frac{G_i^-}{G_i^+ + G_i^-}, \quad 0 \leq G_i \leq 1 \qquad (7)$$

3.4 Sensitivity Analysis

This step assesses the stability of the Optimal Supplier-Hub pairing by subjecting the BWM weights to controlled perturbation. The analysis focuses on the three most dominant criteria identified by the BWM: D1 (DPP Fields Available), C1 (% Water Reuse) and H1 (Cost per Returned Unit). The TOPSIS ranking is tested by systematically adjusting the weight of one dominant criterion by ±20% while proportionally redistributing the remaining weights within that pillar to maintain the sum of 1.0000 (Liang, 2021). The primary goal is to confirm that the optimal choice remains invariant, thereby verifying the robustness of the decision model against minor variations in stakeholder priority.

4. Results and Discussion

The proposed Hybrid BWM-TOPSIS framework was applied to the decision problem of selecting the optimal supplier-hub pairing for digital-enabled circular returns. The methodology first established the critical importance of key factors through BWM and then utilized TOPSIS to execute the dual ranking process. Prior to ranking, the Veto Rules eliminated Supplier F4 for failing to meet the minimum threshold for DPP readiness (D1 < 70%) and social compliance (S2 > 25%). This preliminary filtering ensures that the final selection is based only on alternatives that meet non-negotiable compliance mandates, a step often overlooked in simplified MCDM models (Darbari et al., 2015). The TOPSIS ranking for the four eligible suppliers (F1, F2, F3, F5) is presented in Table 5. The final rank is determined by the Relative Closeness Coefficient (R_i), where a score of 1.0000 indicates perfect alignment with the PB.

Table 5. TOPSIS Ranking for Eligible Suppliers

Alternative	Distance to PB (G+)	Distance to NB (G−)	Relative Closeness (R_i)	Rank
F1	0.3363	0.5697	0.6288	2
F2	0.8952	0.0000	0.0000	4
F3	0.0000	0.8952	1.0000	1
F5	0.5319	0.3747	0.4133	3

The results clearly identify Supplier F3 as the optimal choice, achieving a perfect R_i score. This is driven by F3's excellent raw scores in the most heavily weighted criteria established by the BWM: D1 = 0.6207 and C1 = 0.5063. This outcome validates the model's objective: suppliers demonstrating proactive investment in digitalization and core circular practices are preferred. The prioritization of D1 (DPP compliance) and C1 (% Water Reuse) in the supplier ranking signifies a strategic shift in supplier selection, moving past traditional economic measures. The dominance of D1 (62.07% within its pillar) is particularly notable, indicating that the ability of a supplier to integrate with mandatory upcoming digital frameworks is a more immediate requirement than incremental improvements in social or secondary environmental factors. This mirrors the global shift in the textile industry, where digital traceability is seen as the primary enabler of future circularity and compliance, especially under the EU's DPP mandate (Carvalho et al., 2025). The TOPSIS ranking for the two reverse-logistics hub options is shown in Table 6.

Table 6. TOPSIS Ranking for Reverse-Logistics Hubs

Alternative	**Distance to PB (G+)**	**Distance to NB (G−)**	**Relative Closeness (Ri)**	**Rank**
H_GZ (Gazipur)	0.0631	0.6386	0.9101	1
H_CT (Chattogram)	0.6386	0.0631	0.0899	2

The Gazipur Hub is the optimal reverse-logistics provider. Its selection is overwhelmingly influenced by the BWM weight assigned to H1 = 0.6126. While H_CT performed marginally better on the low-weighted H3 (Emissions), H_GZ's significantly lower operating cost (as reflected in its smaller G^+ distance) proved decisive, confirming that in complex reverse logistics networks, economic feasibility often outweighs minor environmental gains (Darbari et al., 2015). Hence, the overall decision yields the Optimal Supplier-Hub Pairing of F3 with H_GZ.

To validate the stability of the optimal decision, a sensitivity analysis was performed on the most critical weighting factor D1**,** which carried the highest weight (u^*_{D1}= 0.6207) in the supplier model. The TOPSIS ranking was re-calculated after decreasing the D1 weight by 20% (u_{D1} reduced to 0.4966) and proportionally increasing the weights of the remaining D2 and D3 metrics. The results of this robustness test, alongside the original ranking, are displayed in Table 7.

Table 7. Sensitivity test

Alternative	**Original R_i**	**R_i (D1−20%)**	**Original Rank**	**New Rank**	**Remark**
F1	0.6288	0.5755	2	2	Match
F2	0.0000	0.0000	4	4	Match
F3	1.0000	0.8679	1	1	Match
F5	0.4133	0.4705	3	3	Match

As demonstrated in Table 7, even after a 20% reduction in the priority of the dominant D1 metric, Supplier F3 maintained its Rank 1 position. Since the hub ranking is structurally independent of the supplier criteria, H_GZ also remained the optimal hub. This confirmed the robust invariance of the final selection, establishing high confidence in the recommended pairing of F3 and H_GZ.

Furthermore, the model demonstrates the complexity of achieving a truly circular supply chain. While the framework includes comprehensive social and environmental metrics, the final operational decision is characterized by critical trade-offs:

1. **Digital Readiness vs. Social Metrics:** F3's high score was secured by high D1 and C1 scores, offsetting its low score on the least weighted social metric (S1). The compliance-based Veto Rules provided a necessary baseline for social standards (S2 ≤ 25%), ensuring that while social metrics may not dominate the ranking, they remain a non-negotiable entry barrier (Govindan et al., 2019).
2. **Cost vs. Sustainability in Reverse Logistics:** The hub decision highlights the persistent operational challenge in reverse logistics, where cost (H1) is the overwhelmingly dominant factor (61.26%) compared to secondary logistics emissions (H3). This finding suggests that for circular systems to scale in emerging economies like Bangladesh, the reduction of operational cost remains the critical constraint for achieving economic viability (Darbari et al., 2015).

5. Conclusion

This study successfully developed and applied a novel BWM-TOPSIS framework to solve the integrated decision problem of selecting the optimal supplier and reverse-logistics hub to enable digital-enabled circularity in the highly competitive Bangladesh textiles sector. By operationalizing 12 metrics across three distinct pillars - DPP Readiness, the Social-Circular Index, and Hub Feasibility - the model provides a quantifiable tool for brands navigating emerging global compliance mandates. The BWM weighting revealed clear strategic priorities: supplier performance is dominated by DPP Fields Available (D1 = 0.6207) and Water Reuse (C1 = 0.5063), while the hub decision is overwhelmingly driven by Cost per Returned Unit (H1 = 0.6126). The TOPSIS ranking identified Supplier F3 and the Gazipur Hub (H_GZ) as the optimal pairing, demonstrating that suppliers investing early in digital traceability and core environmental efficiency gain a competitive advantage. Crucially, the framework's holistic approach was validated as the mandatory Veto Rules ensured social compliance and the sensitivity analysis confirmed the robust stability of the optimal pairing. While this study offers a feasible prototype for complex circular procurement decisions, the model has limitations, relying on subjective BWM input from a single expert and using a small, localized data sample. Future research should extend the framework using a Fuzzy-BWM approach to capture inherent expert uncertainty and scale the model globally by integrating blockchain technology for real-time DPP metric validation and auditable reporting.

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