

Beyond Import Scale: An Entropy-TOPSIS Framework for Prioritizing Import-Related Supply-Chain Vulnerability in Bangladesh Manufacturing

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Abstract

This study proposes and implements a multi-criteria decision-making framework to evaluate and prioritize import-related supply chain vulnerabilities among eight strategically important manufacturing input categories in Bangladesh. The analysis utilizes a source-verified panel dataset consisting of 40 monthly observations for each category from January 2023 to April 2026, including HS27 Mineral Fuels & Oils, HS29 Organic Chemicals, HS39 Plastics & Articles, HS40 Rubber & Articles, HS52 Cotton, HS72 Iron & Steel, HS84 Machinery & Parts, and HS85 Electrical Machinery. This eight group are significant. Vulnerability is assessed using five dimensions: Exposure, Volatility, Growth pressure, Shock intensity, and Persistence (EVGSP). Objective criterion weights are determined through the Entropy method, while the TOPSIS approach is applied to generate a comparative vulnerability ranking. The results show that Shock intensity has the highest contribution (0.3074), followed by Volatility (0.2887), Exposure (0.1606), Persistence (0.1362), and Growth pressure (0.1071). HS27 Mineral Fuels & Oils emerges as the most vulnerable category with the highest TOPSIS closeness coefficient (0.9724), followed by HS84 Machinery & Parts (0.3336) and HS72 Iron & Steel (0.2914), whereas HS39 Plastics & Articles demonstrates the lowest vulnerability level (0.1307). Statistical validation by one-way ANOVA confirms significant differences in average monthly import values among the selected categories ($F(7,312)=212.67$, $p<0.001$, $\eta^2=0.827$). Furthermore, an exploratory regression analysis reveals that Exposure and Shock collectively explain 95.2% of the variation in TOPSIS scores; however, the limited number of alternatives restricts causal interpretation. The Sensitivity analysis using equal weighting, CRITIC weighting, and criterion elimination demonstrates strong consistency with the original ranking, with CRITIC based results achieving a Spearman correlation coefficient of 0.929. The findings demonstrate that import dependency alone is insufficient for vulnerability assessment, as instability and sudden shocks significantly influence supply chain risk prioritization. The proposed framework provides a systematic early-warning mechanism to support procurement planning, inventory management, and strategic import monitoring while avoiding unsupported conclusions regarding actual shortages or production disruptions.

Keywords: Bangladesh, manufacturing imports, supply chain vulnerability, entropy, Bangladesh trade & economy, Supply chain resilience & early warning, TOPSIS, CRITIC, MCDM.

1. Introduction

1.1 Background and motivation

A country's competitiveness in manufacturing depends on the continuity, affordability, and predictability of imported production inputs. For Bangladesh, the list of imported production inputs includes machinery, equipment, metals, polymers, fuel, chemicals, and textile raw materials, among others, and the volatility

of these imports influences the projection, timing, and cost estimation of any production cycle. So It follows that the decision of what falls under the category of the most significant imports is not linked to the importance of addressing the threats to the stable supply of any category and the volatility accompanying it. Instead, it requires comparing the size of different categories and assessing their impact on production on a unified scale.

Supply-chain resilience is defined as a “capability to prepare for, respond to and recover from disruption while maintaining an acceptable level of performance” (Ponomarev & Holcomb, 2009). Because of the complex nature of both vulnerability and resilience, quantitative treatment of them is less developed than conceptual analysis in this area (Carvalho et al., 2016). Multi-criteria decision-making (MCDM) approaches have therefore been utilized to evaluate the supplier and resilience options under different criteria that are often conflicting (Leong et al., 2022; Mohammed et al., 2021). Monthly foreign-trade statistics published by the Bangladesh Bureau of Statistics (BBS) offer a reproducible basis for this kind of decision support. Import value, however, combines quantity, price and exchange-rate effects, so it indicates expenditure exposure and temporal instability rather than direct evidence of physical shortage, supplier failure or production stoppage. This paper therefore adopts the bounded term import-related supply-chain vulnerability throughout.

Recent Bangladesh-specific evidence shows how dependence on imported or externally constrained inputs becomes an operational vulnerability. Islam, Mim, et al. (2025) report that disruptions in imported maize and soybean meal raise poultry feed costs and constrain availability, while Vhuiyan et al. (2025) identify raw material shortages and transportation delays as linked bottlenecks in the light-engineering sector. In the RMG sector, unreliable energy supply disrupts production schedules and increases operating costs (Islam et al., 2024), and container shortages, tariff conflict and weak digital logistics create additional cost and delay exposure (Islam, Sami, et al., 2025).

Demand side shocks and it can propagate through the same networks. Conflict related boycotts have altered brand demand, retail stocking and local substitution in the Bangladesh beverage market (Bristi et al., 2025; Zaman et al., 2025), while the plastics sector's reliance on imported polymer granules illustrates how material dependence can coexist with underdeveloped local alternatives (Zakir et al., 2025). Together these findings support treating vulnerability as a combination of scale, instability, substitution constraints and exposure to external shocks.

1.2 Related scholarship and research gap

TOPSIS ranks alternatives by their proximity to a positive ideal solution and distance from a negative ideal solution also give idea. The method remains popular in supply-chain research because it is transparent and produces an interpretable closeness coefficient. Integrated supplier-resilience studies have similarly emphasized sensitivity analysis and managerial validation (Leong et al., 2022; Mohammed et al., 2021).

Objective weighting schemes can reduce reliance on expert judgment alone. The Entropy assigns greater weight to criteria that discriminate more strongly among alternatives (Chen, 2020, 2021), while CRITIC combines contrast intensity with inter-criterion conflict (Diakoulaki et al., 1995). A high objective weight signals information dispersion rather than universal managerial importance, so comparing Entropy, equal and CRITIC weights tests whether the conclusions depend excessively on a single weighting philosophy and the result.

Recent Bangladeshi focused applications also support combining decision models with causal and structural analysis. Chowdhury et al. (2025) integrated transportation cost algorithms with DEMATEL to distinguish cost-efficient routes from causal logistics constraints, while Juthi et al. (2025) used ISM to order interdependent policy, coordination and technology strategies. Digital SCM studies further indicate that improved visibility and decision support are possible, but adoption remains constrained by cost, infrastructure and skills gaps among SMEs and RMG firms (Hai et al., 2024; Islam, Debnath, et al., 2025).

This analysis is motivated by the three gaps: a large portion of the supply chain MCDM literature relies on expert scores rather than updatable secondary data; scale only evaluations ignore volatility, shocks, and persistence; and official monthly trade announcements do not prioritize strategic inputs. As shown in Figure 1, the strategy created here uses observed monthly trade values for eight critical HS categories to overcome these gaps.

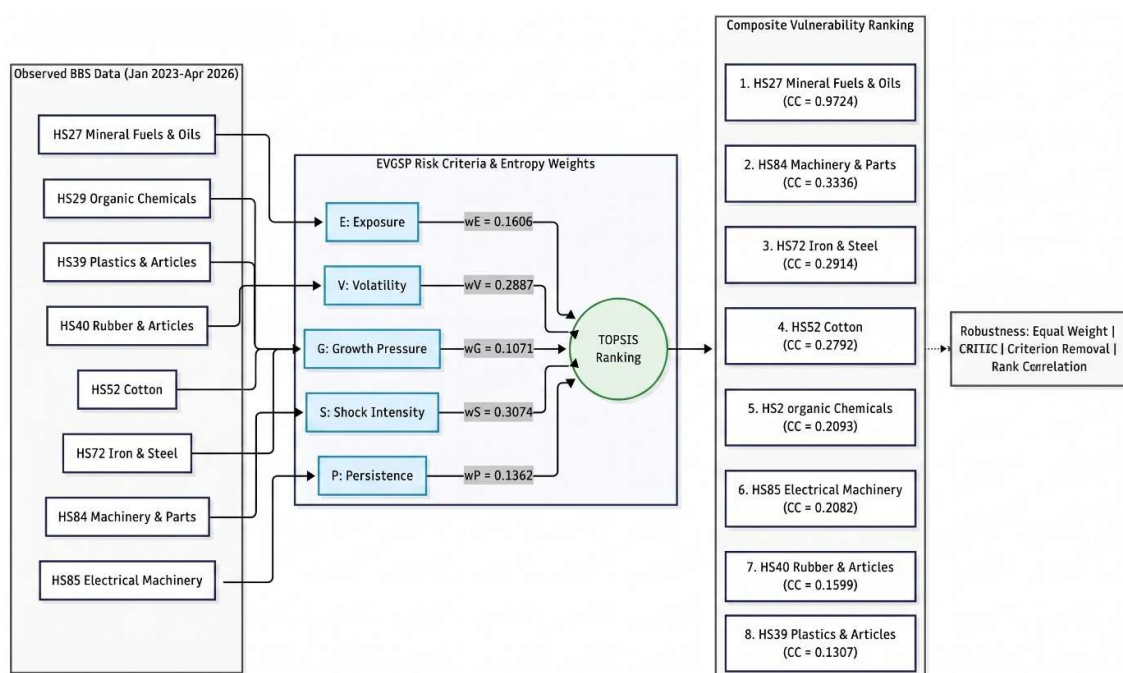


Figure 1: Conceptual framework connecting risk-management measures with BBS monthly trade data

1.3 Research problem, objectives and questions

A rank order based only on magnitude may mislead as a group of large import categories may be stable, whereas a smaller category may exhibit erratic fluctuations or steady year-on-year growth. This paper constructs and validates a transparent framework that transforms monthly import values into five non-redundant criteria, derives objective Entropy weights, ranks eight HS groups using TOPSIS approach and tests for stability of that ranking with equal weights, with CRITIC weights and with criterion-removal scenarios.

Overall, these sector-specific studies identify individual disruptions, technologies or industries, but do not offer an updatable cross-category vulnerability ranking on the basis of an official monthly import panel (Chowdhury et al., 2025; Hai et al., 2024; Islam, Mim, et al., 2025; Vhuiyan et al., 2025). This unresolved comparison hurdle has motivated the current EVGSP-Entropy-TOPSIS framework.

This analysis tackles these issues through five questions: Which group carries the highest composite vulnerability? Which EVGSP dimensions distinguish most strongly between groups? Does the composite ranking deviate from a magnitude-only view? Does the ordering remain stable under different weighting schemes and criterion specifications? Which procurement and policy responses fit the observed risk profiles?

1.4 Contribution

The contribution of this study is not a new Entropy or TOPSIS algorithm. Rather, it lies in integrating a source-audited, 40-month BBS panel with an interpretable EVGSP risk structure, objective weighting, robustness testing and action oriented interpretation tailored to Bangladesh manufacturing and process.

Accordingly, the study complement prior Bangladesh research by moving from single sector or event specific diagnosis toward a repeatable early warning comparison across strategic import groups (Bristi et al., 2025; Islam, Debnath, et al., 2025; Juthi et al., 2025; Zakir et al., 2025).

2. Method

2.1 Data source, sample and analytical units

The empirical source is the BBS Foreign Trade Statistics monthly merchandise-import series. The balanced panel covers January 2023-April 2026 and contains 40 observations for each of eight HS chapters, or 320 group-month observations. Values are expressed in million Taka. Source report and validation status fields are retained in the master workbook so that repeated values, revisions and cross table discrepancies remain auditable.

Table 1. Strategic manufacturing input groups

HS	Input group	Manufacturing relevance
HS27	Mineral Fuels & Oils	Industrial energy and petroleum related production support
HS29	Organic Chemicals	Chemicals, pharmaceuticals, textiles, plastics and coatings
HS39	Plastics & Articles	Packaging, components and industrial intermediates
HS40	Rubber & Articles	Seals, tires, footwear and industrial components
HS52	Cotton	Textile and apparel raw/intermediate material
HS72	Iron & Steel	Fabrication, engineering, construction and machinery inputs
HS84	Machinery & Parts	Capital equipment, production lines, components and spares
HS85	Electrical Machinery	Motors, controls, electrical components and automation equipment

2.2 Data preparation and quality control

A particular two digit scheme of the HS definition and a particular label of the calendar month were applied universally, monetary units were expressed in a million Taka, blanks, missing observations, and genuine zeros were treated differently, abrupt percentage changes were scrutinized to the source report, and finally, the data set was frozen before the MCDM. The descriptive statistics were calculated along with chronological changes of month-to-month and year-on-year before constructing the decision matrix.

2.3 EVGSP measures

Exposure is measured as a group's share of the combined imports of the eight selected groups, since a complete national monthly import denominator was not available in the master workbook; it is therefore a within-basket scale measure. Volatility is the coefficient of variation of the 40 monthly values. Growth is the median of 28 year-on-year changes. Shock is the largest absolute month-to-month change; and Persistence is the proportion of positive year-on-year comparisons. All criteria are oriented so that larger values indicate greater vulnerability.

Table 2. EVGSP criterion definitions

Code	Criterion	Operational definition	Direction
E	Exposure	40-month share of the selected import basket	Higher = greater vulnerability
V	Volatility	Standard deviation divided by mean	Higher = greater vulnerability
G	Growth	Median year-on-year percentage change	Higher = greater vulnerability
S	Shock	Maximum absolute month-to-month percentage change	Higher = greater vulnerability
P	Persistence	Share of positive year-on-year comparisons	Higher = greater vulnerability

$$E_i = \Sigma_t I_{it} / \Sigma_i \Sigma_t I_{it} \quad (1)$$

$$V_i = \sigma_i / \mu_i \quad (2)$$

$$G_i = \text{median}[(I_{it} - I_{it-12}) / I_{it-12}] \quad (3)$$

$$S_i = \max_t |(I_{it} - I_{it-1}) / I_{it-1}| \quad (4)$$

$$P_i = (1/(T-12)) \sum_t 1(g_{it}^{yoy} > 0) \quad (5)$$

2.4 Entropy weighting

Following Shannon (1948), let $X = [x_{ij}]$ denote the 8×5 decision matrix. Each criterion is min-max normalized to z_{ij} and converted to proportions p_{ij} . With $m = 8$, Entropy e_j , divergence d_j and weight w_j are calculated as follows; a criterion receives a larger weight when it carries more cross-alternative information.

$$p_{ij} = z_{ij} / \sum_i z_{ij} \quad (6)$$

$$e_j = -k \sum_i p_{ij} \ln(p_{ij}), k = 1/\ln(m) \quad (7)$$

$$d_j = 1 - e_j, w_j = d_j / \sum_j d_j \quad (8)$$

2.5 TOPSIS and robustness analysis

Following the TOPSIS formulation of Hwang and Yoon (1981), the EVGSP matrix is shifted where necessary to remove negative criterion values, vector-normalized and multiplied by the Entropy weights. Because all criteria represent greater vulnerability, the positive ideal contains each criterion maximum and the negative ideal contains each minimum. Euclidean distances S_i^+ and S_i^- produce the closeness coefficient CC_i , and alternatives are ranked in descending order.

$$r_{ij} = x'_{ij} / \sqrt{\sum_i x'^2_{ij}}, v_{ij} = w_j r_{ij} \quad (9)$$

$$S_i^+ = \sqrt{\sum_j (v_{ij} - v_j^+)^2}, S_i^- = \sqrt{\sum_j (v_{ij} - v_j^-)^2} \quad (10)$$

$$CC_i = S_i^- / (S_i^+ + S_i^-) \quad (11)$$

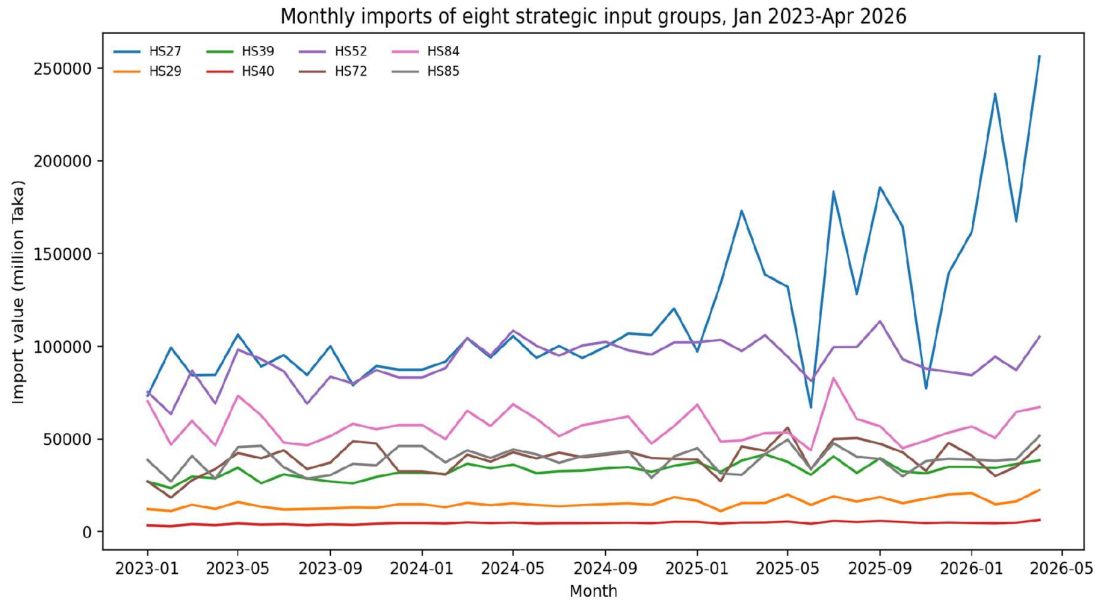
Robustness is evaluated with equal-weight TOPSIS, CRITIC-weight TOPSIS and one-at-a-time criterion removal. Spearman rank correlation compares every scenario with the Entropy base ranking. CRITIC weights are derived from each normalized criterion's contrast intensity and its conflict with the other criteria.

$$C_j = \sigma_j \sum_k (1 - r_{jk}), w_j^{critic} = C_j / \sum_j C_j \quad (12)$$

3. Results

3.1 Import patterns

The four series of forty months have significant differences in both magnitude and temporal behavior. The biggest and most volatile category is Mineral Fuels & Oils. Cotton is large and relatively stable. Machinery & Parts and Iron & Steel are the middle categories. Rubber & Articles is the smallest of all categories. In general, the time window covers several change points missed by a shorter focal period.



Figure

2 shows the eight strategic input groups' monthly imports, one by one, from January 2023 to April 2026

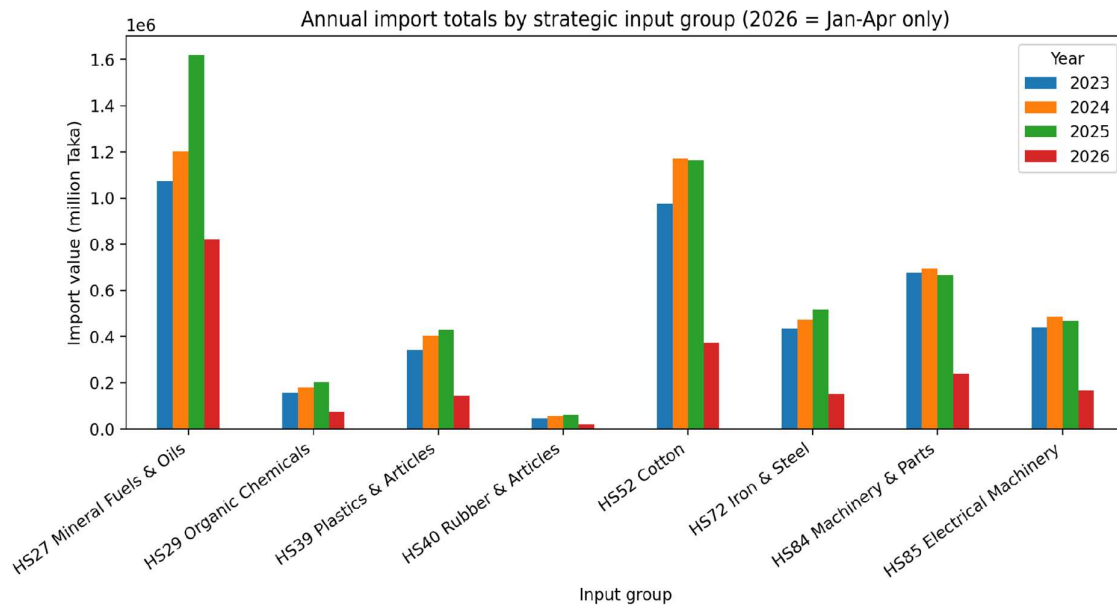


Figure 3. Annual import totals by strategic input group 2026 includes January-April only.

Table 3. Descriptive statistics for monthly imports

Group	Mean	Median	SD	CV	Min	Max
HS27	117,946	100,136	43,281	0.367	67,120	256,181
HS29	15,286	14,826	2,701	0.177	11,129	22,554
HS39	33,044	32,610	4,173	0.126	23,554	41,739
HS40	4,602	4,608	706	0.153	2,963	6,409
HS52	92,108	94,392	11,268	0.122	63,473	113,508
HS72	39,345	39,947	7,674	0.195	18,402	56,000
HS84	56,905	56,901	8,644	0.152	43,953	82,993
HS85	39,022	39,284	6,227	0.160	27,069	51,674

Note that values except CV are in million Taka; n = 40 months per group.

HS27 has the highest value of monthly mean which is 117946 million taka and the highest coefficient of variation which is 0.367. Conversely, second monthly mean is 92108 Million Taka for cotton with lowest coefficient of variation 0.122. The bigger the scale is, the lower the degree of variation is not necessarily not true.

40-month import-share composition of eight strategic input groups

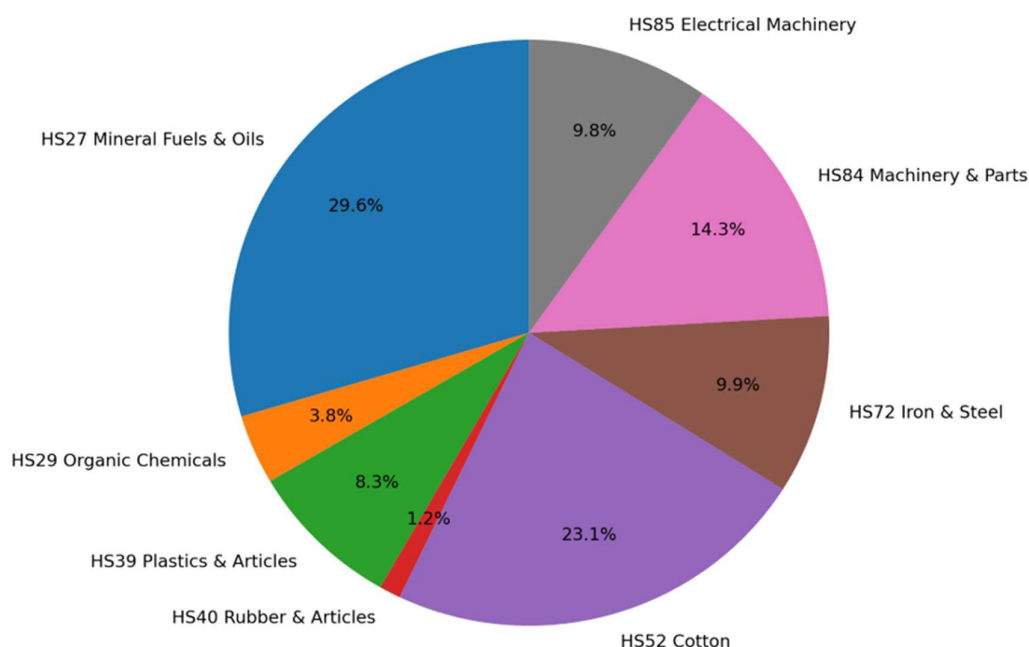


Figure 4. Composition of the selected strategic import groupbasket, January 2023-April 2026.

It has been found that the basket of goods selected is not balanced. More than half of the total amount included there is accounted for by HS27 Mineral Fuels & Oils (29.62%) and HS52 Cotton (23.13%) while another category (HS84 Machinery & Parts) accounts for only 14.29% of the total amount. Thus the first two categories are quite different from

each other and also from the third. Therefore the variation coefficient for these goods is also quite different and these should be treated separately.

The comparison was performed using normalization within group, which permits the analysis of the difference in the distribution shape despite the significant differences in the amount of goods imported. The results of the analysis support the original hypothesis of significant difference between the categories. In particular, HS27 has the largest dispersion and range, and HS52 and HS39 have similar, relatively narrow spreads (see Appendix C, Figure C1 for details).

3.2 statistical analysis

3.2.1 Descriptive statistics

The breadth and volatility of monthly import volumes across the eight strategic input categories varied significantly, according to Table 3's descriptive statistics. First, HS27 Mineral Fuels & Oils has the highest monthly mean (117,946 million Taka) and median (100,136) among all imported commodities. Furthermore, this group has the largest coefficient of variation (CV) of any category, at 0.367, and a standard deviation (SD) of 43,281 million. In compared to other categories, HS52 Cotton has the second-largest mean (92,108 million Taka) and median (94,392), but its SD is the lowest at 0,122. Conversely, HS84 Machinery & Parts falls in the middle of the distribution range, with a mean of 56,905 million and a maximum of 82,993. The lowest mean is 39,345 for HS72 Iron & Steel, yet the SD is only 0.195. Similar to the preceding category, HS85 Electrical Machinery has a mean of 39,022 and an SD of 0,160. HS29 Organic Chemicals has a moderate SD (CV = 0.177), while HS39 Plastics & Articles is somewhat steady (CV = 0.126). Lastly, HS40 Rubber & Articles is the smallest category, with a mean of 4,602 and a range of 2,963 to 6,409, which is more than double the category's mean.

3.2.2 One-way ANOVA and robust test

A one way ANOVA tested whether mean monthly import exposure differs among the eight strategic groups. The null hypothesis states that the all eight population means are equal. The alternative states that at least one group mean differs. The reconstructed ANOVA results are presented below.

Table 4. One-way ANOVA of monthly import values by strategic input group

Source	Sum of squares	df	Mean square	F	Sig.
Between groups	408,985,357,180	7	58,426,479,597	212.672	< .001
Within groups	85,714,398,588	312	274,725,637		
Total	494,699,755,768	319			

The equality-of-means null hypothesis is rejected since the ANOVA is significant ($F(7, 312) = 212.672, p < .001$). With eta-squared and omega-squared of .827 and .822, respectively, group membership accounts for a significant portion of the variation in the monthly import values. Welch's test, which likewise produced a significant result, $F(7, 120.64) = 1111.187, p < .001$, is reasonable given the unequal group variances. The alternative hypothesis is supported by the significant total effect size. It does not, however, indicate which pair of means differs because it is an omnibus test.

To report the exact pairwise differences, a post-hoc analysis using the raw data and the SPSS software should be performed. GamesHowell is an appropriate multiple comparison test given the unequal variances and sample sizes.

3.2.3 Exploratory regression analysis

The effectiveness of selected-basket exposure and maximum month-to-month shock in explaining variation in the TOPSIS closeness coefficient was evaluated using an exploratory multiple regression. Since TOPSIS closeness is determined from EVGSP inputs, the model is meant to be a diagnostic decomposition of the composite score rather than an independent causal model.

Table 5. Exploratory regression model summary

R	R-squared	Adjusted R-squared	Std. error	F	df1	df2	Sig.
.976	.952	.933	.0700	50.049	2	5	< .001

Table 6. Regression coefficients for TOPSIS closeness

Predictor	B	Std. error	Standardized beta	t	Sig.	VIF
Constant	-.068	.046	-	-1.469	.202	-
Exposure	.560	.412	.198	1.359	.232	2.236
Shock	.475	.085	.819	5.618	.002	2.236

With an R-squared of .952 and an adjusted R-squared of .933, the model is in fact significant ($F(2, 5) = 50.049, p < .001$). After adjusting for the confounding variable, the effect of exposure (standardized beta = .198, $p = .232$) is positive but not statistically significant, whereas the effect of shock (standardized beta = .819, $p = .002$) dominates the results. Because each variable has a VIF score of 2.236, which is below the threshold of concern, the analysis is generally secure from collinearity. However, the eight-case sample size is too small to draw firm conclusions about practical significance. Overall, the outcome supports the hypothesis that the extreme HS27 score is more affected by rapid instability than by scale. The result should not be taken as evidence that operational disturbances are caused by the shock source. The finding will must not be interpreted as proof that the source of shock causes operational disruptions or that the model replicates an independent outcome.

3.3 EVGSP decision matrix.

Table 7. EVGSP decision matrix

Group	E	V	G	S	P
HS27	0.2962	0.3670	0.2133	1.7325	0.7857
HS29	0.0384	0.1767	0.1540	0.3876	0.8929
HS39	0.0830	0.1263	0.0796	0.3246	0.7143
HS40	0.0116	0.1533	0.1324	0.3739	0.7857
HS52	0.2313	0.1223	0.0964	0.4212	0.6071
HS72	0.0988	0.1950	0.1092	0.6823	0.6786
HS84	0.1429	0.1519	0.0123	0.8882	0.5000
HS85	0.0980	0.1596	0.0606	0.5987	0.5357

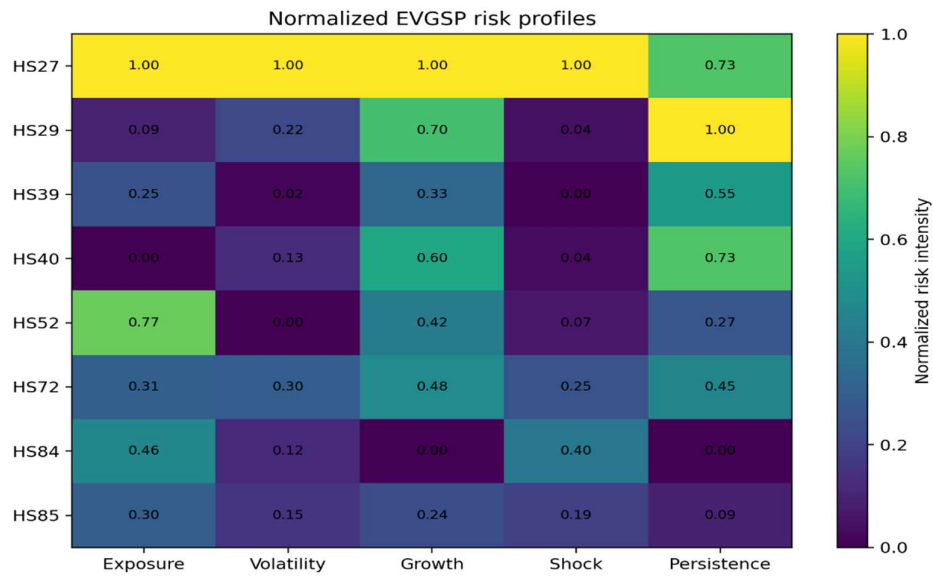


Figure 5. Normalized EVGSP risk profiles across the eight alternatives.

The correlation diagnostic shows a significant but unfinished dependence pattern between growth and persistence ($r = 0.82$) and between volatility and shock ($r = 0.92$). There are conceptual differences between the four measures: Growth collects the median year-over-year growth, Shock captures the largest monthly change, Persistence captures the percentage of times the year-over-year gain has been positive, and Volatility captures the overall dispersion (complete matrix in Appendix C, Figure C2).

3.4 Entropy weights and TOPSIS ranking

Table 8. Entropy-derived criterion weights

Criterion	Entropy	Divergence	Weight
Exposure	0.8368	0.1632	0.1606
Volatility	0.7065	0.2935	0.2887
Growth	0.8911	0.1089	0.1071
Shock	0.6875	0.3125	0.3074
Persistence	0.8615	0.1385	0.1362

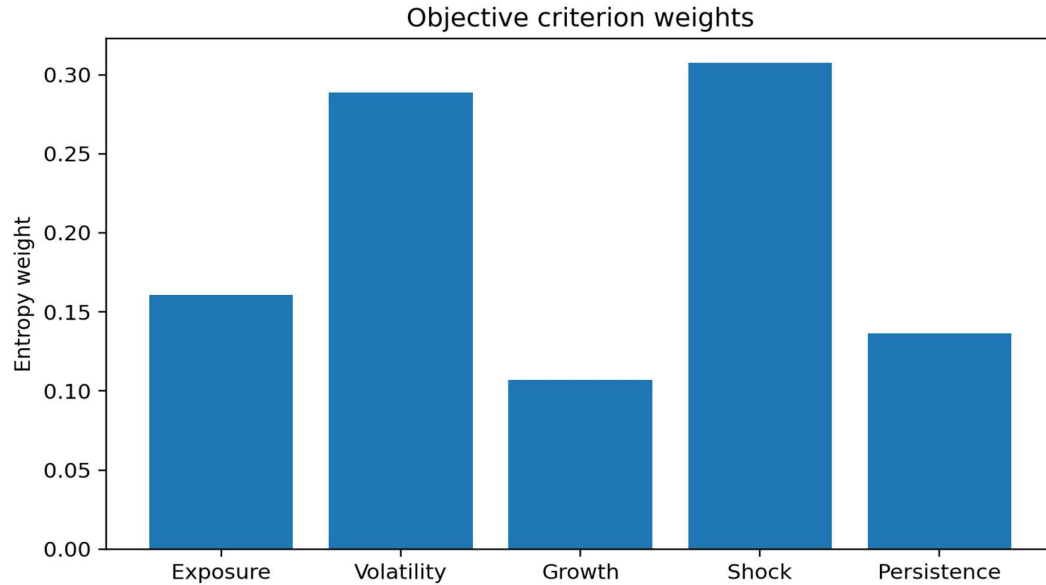


Figure 6. Entropy derived objective criterion weights.

The highest weight is given to shock (30.74%), followed by volatility (28.87%). The biggest differentiation in this matrix is provided by rapid movements and instability, which together account for 59.61% of the base weighting; nonetheless, this does not establish a universal managerial preference.

Table 9. Entropy-TOPSIS vulnerability ranking

Rank	HS	Input group	S+	S–	CC
1	HS27	Mineral Fuels & Oils	0.0074	0.2602	0.9724
2	HS84	Machinery & Parts	0.1827	0.0915	0.3336
3	HS72	Iron & Steel	0.1863	0.0766	0.2914
4	HS52	Cotton	0.2233	0.0865	0.2792
5	HS29	Organic Chemicals	0.2284	0.0604	0.2093
6	HS85	Electrical Machinery	0.2081	0.0547	0.2082
7	HS40	Rubber & Articles	0.2403	0.0457	0.1599
8	HS39	Plastics & Articles	0.2448	0.0368	0.1307

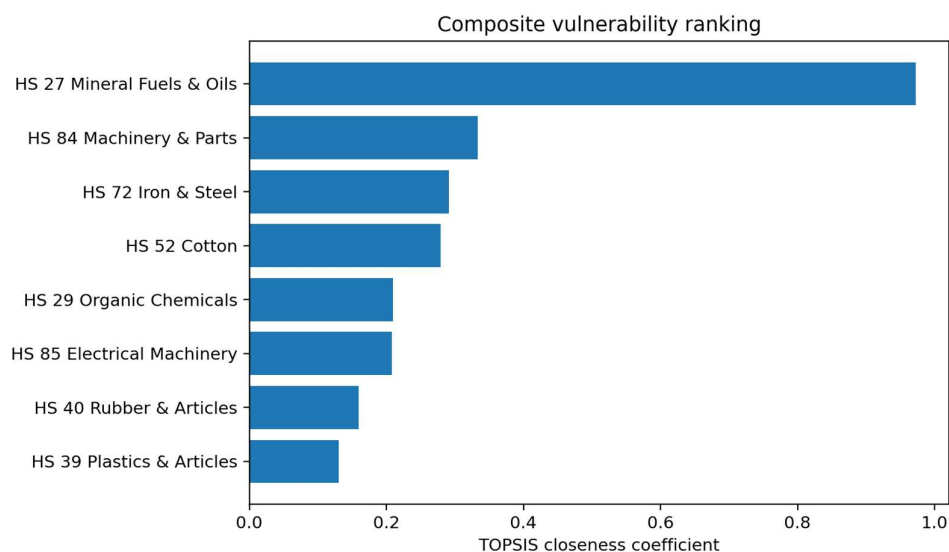


Figure 7. Entropy-TOPSIS composite vulnerability scores.

With a CC of 0.9724, Mineral Fuels & Oils is unquestionably the top group, much ahead of Iron & Steel (0.2914) and Machinery & Parts (0.3336). Because of its relatively steady monthly values, cotton comes fourth despite its vast scale. The exact middle-rank ordering of Organic Chemicals and Electrical Machinery should be regarded with caution because their scores are nearly equal.

3.5 Robustness assessment

Table 10. Rank robustness under alternative specifications

Scenario	Spearman ρ	HS27 rank	HS84 rank	HS72 rank
Entropy	1.000	1	2	3
Equal weights	0.810	1	5	3
CRITIC	0.929	1	3	4
Remove E	0.857	1	2	3
Remove V	0.952	1	2	4
Remove G	0.952	1	2	3
Remove S	0.810	1	5	3
Remove P	0.976	1	2	3

CRITIC is equal to 0.929, criterion-removal correlations range from 0.810 to 0.976, and equal-weight TOPSIS correlates at 0.810 with the starting ranking. In every scenario, HS27 is ranked first, however when Shock or Exposure are given less weight, the intermediate ranks shift. These findings show that the eight groups' exposure to imports varies greatly and that the ordering based just on the scale is very different from the composite ranking. Additionally, since HS27 has the highest proximity coefficient and is ranked top on volatility, growth pressure, and shock, they propose that higher levels of these factors will increase composite susceptibility. The criterion-removal results demonstrate that the main ranking is fairly stable across all specifications, with the caveat that the middle ranks are more sensitive to changes in the specification than the top rank. The alternative-weight correlations verify that Entropy-TOPSIS has significant concordance with equal-weight and CRITIC-weight TOPSIS.

There is clear evidence that the composite ranking deviates from a scale-only viewpoint when exposure and closeness are compared. Because of its low volatility, HS52 has the biggest exposure but only ranks fourth in terms of composite

vulnerability; in contrast, HS84 has a lesser exposure but is placed second due to its relatively higher Shock score. On both scales and composite hazards, HS27 is the anomaly.

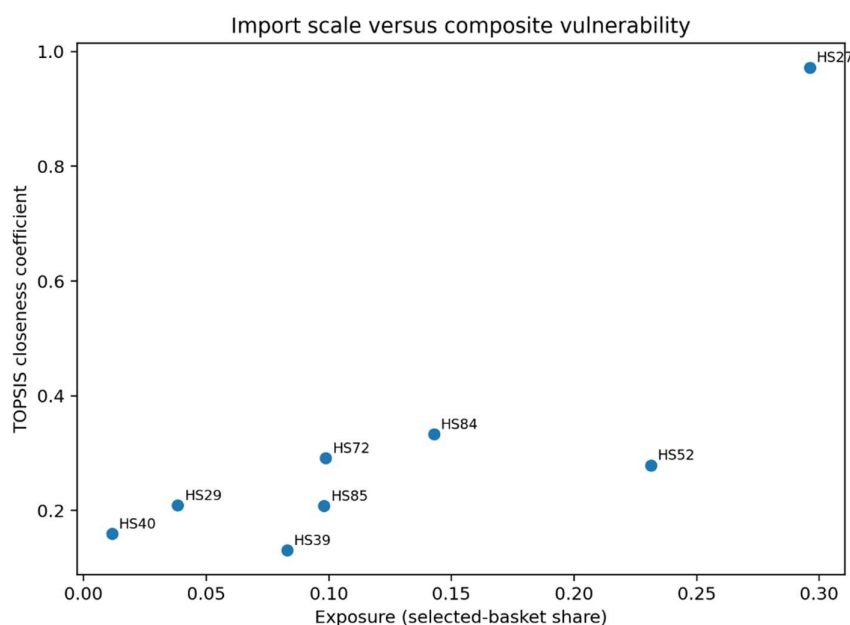


Figure 8. Import scale versus composite vulnerability

3.6 Mann-Kendall Trend Test Results for Strategic Import Groups

The Mann-Kendall non-parametric trend test was applied to identify whether each strategic import category shows a statistically significant monotonic increase or decrease over time.

Hypotheses:

H0: No significant monotonic trend exists.

H1: A significant increasing or decreasing trend exists.

Significance level: $\alpha = 0.05$.

A positive Z value indicates an increasing trend, while a negative Z value indicates a decreasing trend.

HS Group	S Statistic	Kendall Tau	Z Value	p-value	Trend
HS27 Mineral Fuels & Oils	444	0.5692	5.1621	2.44e-07	Increasing
HS29 Organic Chemicals	448	0.5744	5.2087	1.9e-07	Increasing
HS39 Plastics & Articles	386	0.4949	4.4863	7.25e-06	Increasing
HS40 Rubber & Articles	418	0.5359	4.8591	1.18e-06	Increasing
HS52 Cotton	218	0.2795	2.5286	0.01145	Increasing
HS72 Iron & Steel	186	0.2385	2.1557	0.0311	Increasing
HS84 Machinery & Parts	-26	-0.0333	-0.2913	0.77081	No significant trend

HS85 Electrical Machinery	68	0.0872	0.7807	0.43496	No significant trend
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For the majority of strategic import categories, the Mann-Kendall results verify the existence of notable rising trends. There were statistically significant increase trends in HS27 Mineral Fuels & Oils, HS29 Organic Chemicals, HS39 Plastics & Articles, HS40 Rubber & Articles, HS52 Cotton, and HS72 Iron & Steel ($p < 0.05$). Over the course of the observation period, neither HS85 Electrical Machinery nor HS84 Machinery & Parts showed statistically significant monotonic trends. Although their monthly numbers might change, there is no statistical evidence to support the general trend. The EVGSP paradigm is further supported by these results. While the Mann-Kendall test separately verifies if long-term directional movement takes place in the monthly series, the Growth and Persistence criteria successfully *capture changes in import behavior*.

4. Discussion

4.1 Interpretation of the ranking

The main outcome is Mineral Fuels & Oils' extraordinary vulnerability profile. In addition to having the highest volatility, median year-over-year growth, and month-to-month shock, its top ranking is not a scale artifact. In line with resilience research that views vulnerability as multifaceted rather than as a single-cost issue, this multi-criterion dominance explains why it stays first when the weighting structure shifts.

Iron & Steel comes in third with a better balanced exposure-volatility-shock profile, while Machinery & Parts comes in second mainly due to sudden temporal movement. The contrary approach is demonstrated by cotton, which has the lowest volatility despite its huge scale. Despite the persistence-intensive nature of organic chemicals, the composite score is limited by their minimal exposure. Additionally, rubber has a tiny base and great persistence, while plastics comes in last due to its volatility and shock type is low.

4.2 Managerial and policy implications

Customized risk mitigation measures are made possible by the established rating. Strict executive control, scenario-driven budgeting, flexible contracting, and alternate sourcing strategies are required for high-priority categories, particularly mineral fuels. On the other hand, machinery requires that parts be categorized as vital spares, that alternative suppliers and framework agreements be pre-approved, and that maintenance and procurement processes be tightly integrated. The requirements for iron and steel are centered on increasing the number of suppliers and carrying out frequent risk assessments. Lastly, consistent forecasting, careful working capital planning, and strategic sourcing strategies are advantageous for cotton, which is characterized by high exposure and low volatility. As a result, long-term demand and contract monitoring can be used to manage categories with persistent but lower exposure instead of the more intense interventions needed for inputs that are extremely vulnerable to shocks.

Profile / groups	Monitoring cadence	Illustrative trigger	Primary response
Shock-dominated: HS27	Monthly; executive review	Large MoM movement or repeated rank 1	Scenario budgets, flexible contracts, contingency sourcing
Capital/spares risk: HS84	Monthly operational review	Sharp import fall/rise or critical-spares gap	Approved alternatives, framework agreements, spares classification
Balanced industrial input: HS72	Monthly/quarterly	Rising CV plus unfavorable demand outlook	Supplier diversification and synchronized demand planning
High exposure, low volatility: HS52	Monthly forecast; quarterly sourcing	Persistent YoY growth or working-capital pressure	Rolling forecasts, longer contracts and financing coordination

Profile / groups	Monitoring cadence	Illustrative trigger	Primary response
Persistent, lower exposure: HS29/HS40	Quarterly	Several consecutive positive YoY observations	Demand review and contract-volume monitoring
Lower composite: HS39/HS85	Quarterly; event driven	Material rank increase or supplier-specific alert	Routine controls, approved alternates and reassessment

BBS releases might be integrated into an updateable strategic-import dashboard at the policy level. The EVGSP criteria and rank modifications might be updated by adding new observations to the database and putting them through the same testing as the initial inputs. While the categories with high shock exposure should be watched for short-term disruptions, the most exposed but stable categories will need to be given priority in terms of long-term capability or substitute analysis. The methodology aids in concentrating on the most important aspects; it does not assess the economic or technological attractiveness of domestic substitute choices.

The most recent value of the measure, its TOPSIS score, rank change, and validation flags for each category should all be displayed on the EVGSP dashboard. In addition to statistical outliers, escalation criteria should take into account inventory cover, supplier lead time, port status, and contract commitments. As a result, an abrupt rise in import value is a signal for more research rather than a crisis.

4.3 Limitations and future research

There are eight primary limitations to the analysis. First, a high Shock score does not necessarily indicate a physical disruption because monetary values incorporate quantities, prices, and exchange rates. Second, because national monthly import totals were not available, exposure is measured inside the chosen basket. Third, the dataset is unable to quantify supplier concentration and does not have a complete commodity-by-country matrix. Fourth, significant product-level variations might be obscured by two-digit HS chapters. Fifth, changes may be made to official trade values. Sixth, not all temporal windows or normalization rules are covered by robustness testing, although alternative weights and criterion removal are. Seventh, there may be slight numerical discrepancies because the ANOVA was rebuilt using rounded group means and standard deviations rather than exported from the unrounded 320-record SPSS dataset. Eighth, only eight group-level instances are included in the regression, which explains .Seventh, there may be slight numerical discrepancies because the ANOVA was rebuilt using rounded group means and standard deviations rather than exported from the unrounded 320-record SPSS dataset. Eighth, the regression is descriptive and cannot prove causation or out-of-sample prediction because it only includes eight group-level examples and explains a score obtained from the same criterion system.

National import totals, quantity and unit-value series, country-by-HS concentration, currency rates, global commodity prices, and firm-level metrics like lead times, inventory days, supplier performance, port delays, and production interruptions should all be included in future studies. These improvements would link trade signals with actual operational results and differentiate external price fluctuations from quantity restrictions..

5. Decision, Conclusion and Recommendations

5.1 Decision synthesis

The primary choice is to designate HS27 Mineral Fuels & Oils as Bangladeshi manufacturing's top import-related vulnerability. Its simultaneous domination in Exposure, Volatility, Growth, and Shock, its TOPSIS proximity coefficient of 0.9724, and its top spot in each alternative-weight and criterion-removal scenario all lend credence to this choice. It should be monitored the most frequently and have the most robust backup plans.

The multi-criteria decision is strengthened but not replaced by the statistical evidence. The regression shows that shock contributes more to variation in the composite score than exposure, while the ANOVA demonstrates that the eight groups have significantly different mean import scales. Because a large but stable category like HS52 Cotton demands a different reaction than a large and unstable category like HS27, decision makers should not consider import size as the only priority rule.

5.2 Managerial recommendations

HS27 should fall under scenario-based budgeting, flexible contracting, monthly executive review, and contingency sourcing for manufacturing companies. Since its second rank is mostly driven by sudden movements, HS84 Machinery & Parts should be handled by framework agreements, approved alternatives, and critical-spares classification. Coordinated demand planning and supplier diversity are necessary for HS72 Iron & Steel. Instead of using emergency controls, HS52 Cotton should be controlled through longer-horizon sourcing, working-capital planning, and rolling forecasts. Regular monitoring of lower-ranked groups should continue, with escalation occurring in response to significant shifts in rank, volatility, or supplier circumstances.

5.3 Policy and implementation recommendations

BBS trade releases should be converted into an updateable strategic-import dashboard that reports the latest EVGSP values, TOPSIS score, rank movement and source-validation status. Each alert should be checked against inventory cover, lead time, port conditions, exchange-rate movements, commodity prices and contract exposure before action is authorized.

5.4 Final conclusion

The EVGSP-Entropy-TOPSIS architecture provides a visible and repeatable prioritizing method for manufacturing vulnerability related to imports. It is helpful in differentiating between instability and scale and transforming complex evidence into discrete acts. The results indicate the necessity for quick attention to HS27 and systematic monitoring of HS84 and HS72, and they demonstrate that HS52 should not be considered equally unstable simply because it is large. The framework continues to function as an early warning layer, identifying situations in which further research is necessary but operational data are still needed before determining that a shortage, supplier failure, or production interruption has happened.

Data availability and ethics statement

There are no human subjects or individually identifiable information used in the study; instead, secondary aggregate trade statistics are used. The source and validation fields are preserved in the analytical master dataset, which was assembled from BBS Foreign Trade Statistics monthly reports. When journal policy allows, the final cleaned workbook and calculation code should be archived with the submitted publication.

References

- Bangladesh Bureau of Statistics. (2023–2026). *Foreign trade statistics: Monthly reports, January 2023–April 2026*. Statistics and Informatics Division, Government of Bangladesh.
- Bristi, K. A., Tamanna, Z. A., Akhand, S. A., Saha, K., & Farha, R. (2025). Impact of the Palestine-Israel war and boycott issue on beverage consumption and supply in Dhaka. *Supply Chain Insider*, 15(1), 15–27. <https://doi.org/10.5281/zenodo.17284266>
- Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., & Cruz-Machado, V. (2016). Resilience and vulnerability in supply chain: Literature review. *IFAC-PapersOnLine*, 49(12), 1444–1450. <https://doi.org/10.1016/j.ifacol.2016.07.775>
- Chen, C.-H. (2020). A novel multi-criteria decision-making model for building material supplier selection based on entropy-AHP weighted TOPSIS. *Entropy*, 22(2), 259. <https://doi.org/10.3390/e22020259>
- Chen, C.-H. (2021). A hybrid multi-criteria decision-making approach based on ANP-entropy TOPSIS for building materials supplier selection. *Entropy*, 23(12), 1597. <https://doi.org/10.3390/e23121597>
- Chowdhury, S. A., Alim, A. B., Soumik, M. H. A., Zaman, S. S., & Shoshi, S. R. (2025). A hybrid approach to logistics optimization: Combining DEMATEL with classical transportation algorithms in the steel industry. *Supply Chain Insider*, 17(1), 120–143. <https://doi.org/10.5281/zenodo.17285052>
- Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The CRITIC method. *Computers & Operations Research*, 22(7), 763–770. [https://doi.org/10.1016/0305-0548\(94\)00059-H](https://doi.org/10.1016/0305-0548(94)00059-H)

- Hai, S. B. A., Uddin, M. J., Rahim, A. R., Haq, N., & Israa, F. (2024). Adoption of digital tools in supply chain management among SMEs in Bangladesh. *Supply Chain Insider*, 12(1), 86–100. <https://doi.org/10.5281/zenodo.13865129>
- Hwang, C.-L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications: A state-of-the-art survey*. Springer-Verlag.
- Islam, K. A. J., Sami, H. A., Choudhury, H. D., Snigdh, A. A., & Islam, M. E. (2025). Triple threats and triple tech: A literature review of container shortage, digital logistics barriers, and tariff wars in modern supply chains and the untapped synergy of IoT, AI, and blockchain for resilience. *Supply Chain Insider*, 16(1), 1–21. <https://doi.org/10.5281/zenodo.17284566>
- Islam, M. A., Debnath, S., Shihab, M. S. A., & Islam, S. (2025). Revolutionizing supply chain management in RMG: A systematic review, AI traditional vs. intelligent systems. *Supply Chain Insider*, 16(1), 36–52. <https://doi.org/10.5281/zenodo.17284625>
- Islam, M. M., Mim, S. K., & Islam, S. (2025). The impact of supply chain disruptions on the cost and availability of poultry feed in Bangladesh, and potential mitigation strategies. *Supply Chain Insider*, 15(1), 28–52. <https://doi.org/10.5281/zenodo.17284344>
- Islam, T., Abrar, A., Mim, M., & Noshin, S. (2024). How to reduce energy crisis of RMG industry in Bangladesh: Overcome utilizing proper supply chain management. *Supply Chain Insider*, 12(1), 101–133. <https://doi.org/10.5281/zenodo.13865148>
- Juthi, I. J., Prithy, N. T., & Jonma, S. I. (2025). Assessing carbon footprint reduction strategies for last-mile delivery in emerging economies: An interpretive structural modelling (ISM) approach. *Supply Chain Insider*, 15(1), 75–92. <https://doi.org/10.5281/zenodo.17284471>
- Leong, W. Y., Wong, K. Y., & Wong, W. P. (2022). A new integrated multi-criteria decision-making model for resilient supplier selection. *Applied System Innovation*, 5(1), 8. <https://doi.org/10.3390/asi5010008>
- Mohammed, A., Naghshineh, B., Spiegler, V., & Carvalho, H. (2021). Conceptualising a supply and demand resilience methodology: A hybrid DEMATEL-TOPSIS-possibilistic multi-objective optimization approach. *Computers & Industrial Engineering*, 160, 107589. <https://doi.org/10.1016/j.cie.2021.107589>
- Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, 20(1), 124–143. <https://doi.org/10.1108/09574090910954873>
- Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, 27(3), 379–423; 27(4), 623–656.
- Vhuiyan, T., Naim, M. N. H., Moni, K. K., Jaher, M. A., & Kiron, M. K. S. (2025). Addressing bottlenecks in Bangladesh's light engineering industry: A comprehensive analysis. *Supply Chain Insider*, 17(1), 65–92. <https://doi.org/10.5281/zenodo.17285008>
- Zakir, M. N. B., Biswas, M. T., Siam, S., & Altafin, R. M. (2025). Toward sustainable alternatives: Analyzing bioplastic supply chain challenges in Bangladesh's local market. *Supply Chain Insider*, 15(1), 93–102. <https://doi.org/10.5281/zenodo.17284506>
- Zaman, M., Hasan, S., Islam, A., & Momen, N. (2025). The impact of consumer boycotts on multinational corporations: A case study of Bangladesh and global brands amid the Israeli-Palestinian conflict. *Supply Chain Insider*, 15(1), 1–14. <https://doi.org/10.5281/zenodo.17284232>

Appendix A. Reproducibility and Update Protocol

This appendix records the minimum information needed to audit, reproduce and update the EVGSP-Entropy-TOPSIS assessment without repeating diagnostics already reported in the Results section.

A1. Minimum reproducibility record

Component	Required record	Reason
Source	BBS report, table, month and retrieval record source	Trace every observation
Definition	Two digit HS code, label and units	Prevent classification drift
Cleaning	Missing value, zero and revision decisions	Make judgment calls auditable
Indicators	Formula, window and denominator for each EVGSP measure	Enable exact recalculation
MCDM	Normalized matrix, weights, ideal points, distances and CC	Reproduce the ranking
Robustness	Alternative weights, omitted criteria and rank correlations	Show assumption sensitivity

A2. Update procedure

- Append the new BBS monthly values using the same HS definitions, month labels and million-Taka unit.
- Record the source report, table, retrieval date, revisions, missing values and validation exceptions.
- Recalculate all five EVGSP indicators using the stated windows and selected-basket denominator.
- Re-estimate Entropy weights and TOPSIS scores; rerun equal-weight, CRITIC and criterion-removal checks.
- Archive the updated matrix, scores, rank changes and any managerial action taken.

A3. SPSS replication settings

- One-way ANOVA: Analyze > Compare Means > One-Way ANOVA; Dependent List = Monthly Import Value; Factor = HS Group; request Descriptives, Homogeneity of Variance, Welch and Games-Howell post-hoc comparisons.
- Linear regression: Analyze > Regression > Linear; Dependent = TOPSIS CC; Independents = Exposure and Shock; request Model Fit, Confidence Intervals, Collinearity Diagnostics and residual plots.

Appendix B. Interpretation and Deployment Safeguards

The model is an early-warning and prioritization layer. It should support, rather than replace, operational verification and managerial judgment.

B1. Interpretation safeguards

- Treat import value as a combined price, quantity and exchange-rate signal, not as physical volume alone.
- Describe Exposure as a share of the selected eight-group basket, not of all Bangladesh merchandise imports.
- Do not infer stock-outs, factory shutdowns or supplier failure without corresponding operational evidence.
- Interpret close middle-rank scores cautiously and review criterion profiles alongside ordinal ranks.

B2. Dashboard and escalation controls

- Display the latest EVGSP values, TOPSIS score, rank and change from the previous update.
- Flag source revisions and validation exceptions before recalculating the decision matrix.
- Separate statistical alerts from operational confirmation and assign an accountable review owner.
- Record the response, rationale and next review date for every escalated signal.
- Re-estimate weights and sensitivity results when the observation window or alternative set changes materially.

These controls preserve an auditable evidence trail while preventing a composite score from being treated as automatic proof of disruption.

Appendix C. Supplementary Diagnostic Figures

This appendix presents two supporting diagnostic figures referenced in Section 3. They are supplementary to the main composite-ranking narrative and are retained here, rather than in the main text, for transparency and reviewer reference.

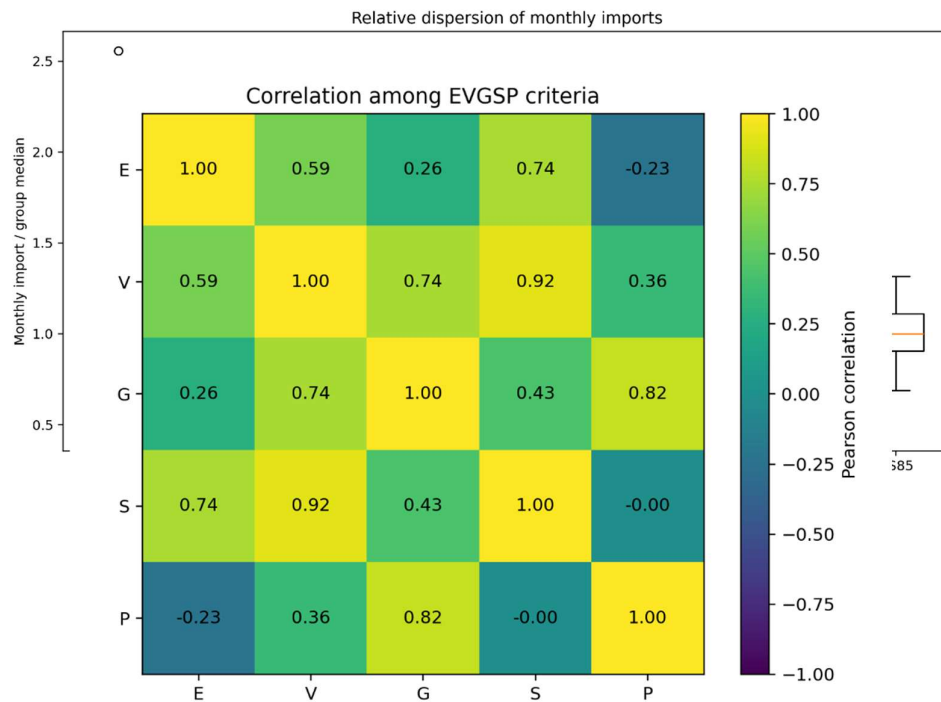


Figure C1. Relative dispersion of monthly imports by strategic input group (within-group normalized boxplot).

Figure C2. Correlation matrix for Exposure, Volatility, Growth, Shock and Persistence.