Business Data Analytics for Sustainable and Resilient Food Procurement: Integrating Expert Judgment and Objective Weighting under Uncertainty

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Abstract

Food manufacturers increasingly face procurement decisions in which sustainability, continuity, food safety, social responsibility, and cost must be evaluated under uncertain and conflicting evidence. This study develops a business data analytics framework for sustainable and resilient food procurement by integrating expert judgment with objective weighting under uncertainty. The framework converts linguistic supplier assessments into uncertainty-aware evaluation scores, combines subjective criteria weights from cross-functional experts with objective weights derived from the information structure of supplier data, and ranks suppliers through a robust multi-normalization scoring process. A food-manufacturing case with six anonymized suppliers demonstrates how the framework identifies a preferred supplier while also generating diagnostics for supplier development, backup sourcing, and resilience investment. Results show that resilience and social responsibility criteria become decisive when supplier continuity, labor compliance, recovery capability, and traceability are explicitly modeled. Sensitivity analysis across subjective-objective weighting scenarios confirms the stability of the leading supplier and reveals where lower-ranked suppliers remain vulnerable. The study contributes to business data analytics by reframing supplier selection as an auditable analytics system rather than a one-time ranking exercise. It also provides managerial guidance for designing sustainable-resilient procurement scorecards, data-governance routines, and supplier improvement portfolios in disruption-sensitive food supply chains.

Keywords: Sustainable procurement; Food supply chains; Business data analytics; Supplier selection; Resilience; Hybrid weighting; Fuzzy decision support; Objective and subjective criteria weighting

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Management Analytics for Industrial Cyber-Risk Detection: Fusing Statistical and Topological Features of IIoT DDoS Traffic

1. Introduction

Food procurement has become a strategic analytics problem rather than a routine purchasing activity. Food manufacturers need reliable suppliers who can deliver safe inputs, keep costs controllable, reduce environmental burden, protect workers, recover from disruptions, and provide transparent traceability records. The challenge is that these requirements rarely move in the same direction. A supplier with the lowest quoted price may show weak labor safeguards or poor continuity capability, while a supplier with strong environmental practices may generate higher short-term procurement cost. Contemporary food supply chains therefore require analytical decision systems that integrate sustainability and resilience into the same business logic (Ahi and Searcy, 2013; Carter and Rogers, 2008; Seuring and Müller, 2008; Beske et al., 2014).

The managerial difficulty is intensified by uncertainty. Supplier information is often incomplete, inconsistent, or expressed linguistically by procurement managers, quality supervisors, logistics specialists, and sustainability officers. Traditional scorecards normally translate these judgments into crisp values too early, causing the loss of hesitation and ambiguity that are inherent in expert assessments. At the same time, purely expert-based methods may reproduce personal bias or department-specific preference. Data analytics can reduce this problem by combining subjective judgment with objective evidence derived from operating data, audit records, delivery performance, rejection rates, and disruption recovery indicators (Choi et al., 2018; Hazen et al., 2014; Schoenherr and Speier-Pero, 2015; Gunasekaran et al., 2017).

This paper develops a business data analytics framework for sustainable and resilient food procurement under uncertainty. It is inspired by fuzzy multi-attribute decision-making logic but reframes supplier selection as an enterprise analytics process that combines expert judgment, objective weighting, and robust ranking. The framework contains five connected phases: criteria governance, fuzzy evidence representation, hybrid weighting, supplier ranking, and managerial review. Rather than treating mathematical ranking as a black-box output, the proposed framework makes each analytical stage interpretable for procurement managers and creates a route for audit, sensitivity analysis, and continuous improvement (Ho et al., 2010; Chai et al., 2013; Mardani et al., 2015; Zavadskas et al., 2014).

The study contributes to business and data analytics in four ways. First, it develops a supplier analytics architecture that converts scattered procurement information into a structured decision process. Second, it uses an uncertainty-aware representation to retain the ambiguity of linguistic judgments without reducing them prematurely to deterministic scores. Third, it combines subjective and objective weighting so that managerial priorities and data-driven variability are both reflected in final criteria importance. Fourth, it demonstrates how ranking outputs can be translated into procurement policy, supplier development, and resilience investment decisions. These contributions are aligned with the broader transition from isolated decision tools to management analytics systems that support industrial and supply-chain decision making (Lu et al., 2024a; Lu et al., 2024b; Lu, 2021; Lu, 2025).

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The remainder of the article is organized as follows. Section 2 reviews the literature on sustainable procurement, resilient food supply chains, big data analytics, and fuzzy multi-criteria decision methods. Section 3 presents the proposed analytical framework. Section 4 describes the data structure, criteria set, and computational design. Section 5 reports a food procurement case study and the ranking results. Section 6 provides robustness and sensitivity analyses. Section 7 discusses managerial implications. Section 8 concludes the paper and proposes future research directions. Figure 1 summarizes the conceptual logic of the article.

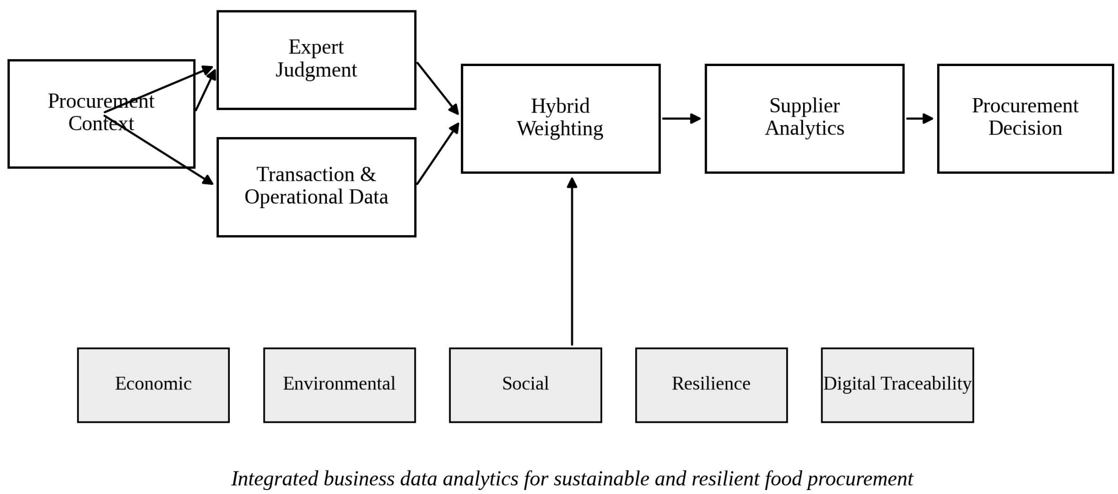

Figure 1. Conceptual framework for business data analytics in sustainable and resilient food procurement.

2. Literature Review

Sustainable supply chain management is grounded in the idea that firms must manage economic, environmental, and social performance simultaneously. Early research moved the field from a narrow green purchasing logic to a broader triple-bottom-line perspective, emphasizing that supply decisions shape emissions, resource use, labor conditions, supplier development, and long-term competitiveness (Carter and Rogers, 2008; Seuring and Müller, 2008; Pagell and Wu, 2009; Pagell and Shevchenko, 2014). In food manufacturing, the sustainability problem is especially salient because upstream agricultural practices affect land use, water stress, chemical inputs, packaging waste, and food loss. Sustainable procurement therefore cannot be treated as an optional compliance requirement; it is an operational capability that connects purchasing decisions with corporate responsibility and supply continuity (Yakovleva, 2007; Verdouw et al., 2016).

Supplier selection research has long used multi-criteria decision-making to evaluate conflicting criteria. Classical approaches such as TOPSIS, VIKOR, PROMETHEE, EDAS, MABAC, and SWARA provide structured methods for comparing alternatives when several criteria must be considered simultaneously (Brans and Vincke, 1985; Opricovic and Tzeng, 2004; Keshavarz Ghorabaee et al., 2015; Pamucar and Ćirović, 2015; Keršuliene et al., 2010). In supplier selection, these methods have been extended with fuzzy logic to accommodate imprecise

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expert judgments. Fuzzy supplier-selection studies show that linguistic assessments can be incorporated into decision matrices without forcing experts to provide unrealistic exact values (Chen, 2000; Chen et al., 2006; Büyüközkan and Çifçi, 2011; Amindoust et al., 2012).

The sustainable supplier selection literature has increasingly combined green, social, and operational criteria. Reviews and empirical applications demonstrate that supplier evaluation requires not only price and quality but also environmental management systems, pollution control, social responsibility, collaboration readiness, innovation capability, and information transparency (Govindan et al., 2015; Zimmer et al., 2016; Luthra et al., 2017; Brandenburg et al., 2014). However, much of this work remains focused on sustainability criteria alone, while resilience criteria are often introduced separately. The food sector needs a more integrated logic because supplier sustainability loses practical value if a supplier cannot maintain continuity during disruptions, and resilience loses legitimacy if it depends on environmentally or socially damaging practices (Ahi and Searcy, 2013; Touboulic and Walker, 2015).

Supply chain resilience is generally understood as the capability to prepare for, respond to, and recover from disruptions. Foundational studies emphasize visibility, flexibility, redundancy, collaboration, agility, and recovery capability as resilience enablers (Christopher and Peck, 2004; Ponomarov and Holcomb, 2009; Pettit et al., 2010; Tukamuhabwa et al., 2015). Later reviews expand this perspective by showing that resilience is not a single attribute but a system-level property involving risk monitoring, adaptive capacity, and coordination among supply chain actors (Hohenstein et al., 2015; Kamalahmadi and Parast, 2016; Ambulkar et al., 2015). Food systems are particularly disruption-sensitive because demand is time-sensitive, storage conditions are restrictive, shelf life is limited, and quality failures can threaten public health.

The COVID-19 pandemic showed that food supply chain disruptions can quickly generate supply shortages, price instability, logistics bottlenecks, and operational shutdowns. Studies of pandemic disruptions highlight the importance of flexibility, local and diversified sourcing, digital visibility, and scenario planning for reducing vulnerability (Ivanov, 2020; Ivanov and Dolgui, 2020; Queiroz et al., 2020; Hobbs, 2020). Food quality and safety risks also increased because firms had to adapt to new sanitation requirements, labor shortages, and changing consumption patterns (Aday and Aday, 2020; Rizou et al., 2020; Galanakis, 2020). These findings justify the inclusion of resilience criteria in supplier evaluation systems for food procurement.

Business data analytics provides the methodological basis for transforming procurement decisions into continuously improving decision systems. Big data analytics capability improves firm performance when it is aligned with business strategy, organizational resources, and dynamic capabilities (Akter et al., 2016; Gupta and George, 2016; Fosso Wamba et al., 2017). In supply chains, analytics supports demand forecasting, inventory control, supplier risk monitoring, logistics optimization, and sustainability measurement (Fosso Wamba et al., 2015; Gunasekaran et al., 2017; Choi et al., 2018; Bag et al., 2020). The present study extends this perspective by treating supplier selection as an analytics process that must accommodate both human judgment and objective evidence.

Digital transformation also changes the boundary of supplier analytics. Digital supply chains rely on interoperable information systems, cloud services, IoT, blockchain, and analytics platforms to convert dispersed data into operational visibility (Büyüközkan and Göçer, 2018; Yu et al., 2018; Kache and Seuring, 2017). Related work on Industry 4.0, industrial information integration, AI, blockchain, IoT security, 6G, and management analytics shows that modern supply chain decision-making increasingly depends on cyber-physical connectivity, trusted data exchange, and algorithmic interpretation (Lu, 2017b; Lu, 2017a; Lu and Xu, 2019; Lu and Zheng, 2020; Chen et al., 2024; Xu et al., 2021). For food procurement, these technologies can provide traceability, auditability, and real-time risk sensing.

Despite these developments, three research gaps remain. First, many supplier selection models still rely mainly on either subjective expert weights or objective data-driven weights, producing either bias from human judgment or managerial irrelevance from purely statistical weighting. Second, resilience and sustainability are often treated as separate evaluation domains rather than interacting criteria. Third, supplier ranking models frequently end with a final score without translating the result into managerial policies, audit routines, or supplier development actions. The present article addresses these gaps by proposing a hybrid business analytics framework that combines expert judgment and objective weighting under uncertainty and connects ranking outcomes to procurement governance (Baryannis et al., 2019; Dubey et al., 2020; Zhang and Lu, 2021; Lu, 2019a).

Additional methodological and supply-chain evidence also informs the analytical design, particularly studies on green procurement, supplier relationship investments, food-chain digitalization, and decision modeling (Dweiri et al., 2016; Govindan and Sivakumar, 2016; Pagell et al., 2007; Pamucar et al., 2018; Lu et al., 2023).

3. Analytical Framework

The proposed framework is designed for food manufacturers that need to select suppliers under ambiguous sustainability, resilience, and performance evidence. It does not assume that all procurement information is crisp, complete, or equally reliable. Instead, it treats supplier evaluation as a layered data analytics process in which expert knowledge, operational data, and uncertainty modeling are integrated into a transparent decision workflow. The architecture is shown in Figure 2.

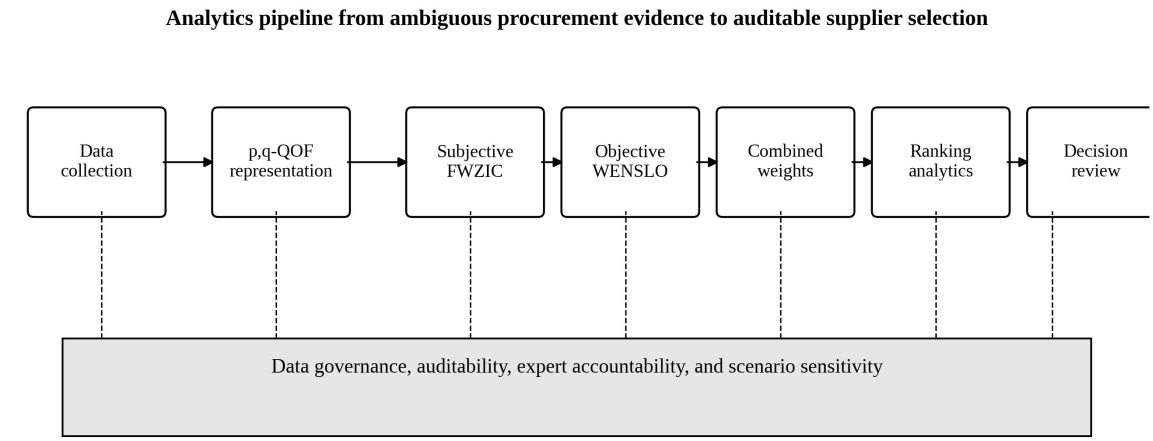

Figure 2. Analytics pipeline integrating expert judgment, objective weighting, supplier scoring, and governance review.

The first stage is criteria governance. Procurement managers identify the decision dimensions and build a criteria hierarchy. In this study the hierarchy contains five dimensions: economic performance, environmental sustainability, social responsibility, resilience capability, and digital traceability. Economic performance reflects price competitiveness, cost stability, and quality reliability. Environmental sustainability captures emissions, waste, resource efficiency, packaging practices, and environmental management. Social responsibility covers labor practices, safety, compliance, and community responsibility. Resilience capability includes delivery continuity, geographic risk, flexibility, inventory recovery, and substitution capacity. Digital traceability refers to data sharing, audit readiness, platform integration, and transparency. This hierarchy responds to the need for multi-dimensional evaluation in sustainable supply chains (Zhu et al., 2005; Rao and Holt, 2005; Vachon and Klassen, 2006; Simpson et al., 2007).

The second stage is evidence representation. Expert assessments are collected through linguistic terms and mapped into uncertainty-aware scores. The purpose is not to imitate a specific fuzzy formalism mechanically, but to preserve the distinction between support, opposition, and hesitation in expert judgments. For example, an expert may strongly support a supplier's continuity capability while still expressing concern about its digital documentation. Conventional crisp scoring cannot capture this asymmetric confidence. In this article, the membership side of a score represents positive support for supplier performance, the non-membership side represents explicit concern, and the residual term represents hesitation or lack of evidence. This representation follows the general logic of fuzzy group decision-making without copying a particular prior model (Chen, 2000; Büyüközkan and Çifçi, 2011).

The third stage is hybrid weighting. Subjective weights are obtained from structured expert judgment, while objective weights are derived from the dispersion and information content of the supplier performance matrix. Expert weights are valuable because managers understand regulatory priorities, customer expectations, and strategic constraints. Objective weights are

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valuable because some criteria show greater discrimination among suppliers and therefore carry more information for ranking. The combined weight for each criterion is calculated as $W_j = \alpha SW_j + (1 - \alpha)OW_j$, where SW_j is the subjective weight, OW_j is the objective weight, and α is the managerial balance parameter. When $\alpha = 0.5$, expert judgment and data variation are treated equally. The parameter can be adjusted in sensitivity analysis to test whether the selected supplier remains stable under different decision philosophies.

The fourth stage is supplier ranking. The framework normalizes supplier performance under multiple normalization logics, constructs a reference profile, estimates distance and relative performance, and then produces a final comprehensive score. Ranking is not treated as the only result. The framework also produces diagnostic outputs: criteria weights, supplier weaknesses, robustness under α variation, and scenario-based ranking stability. These outputs make the model useful for supplier development, not just supplier elimination. A supplier ranked second may still be strategically important if it performs well under disruption scenarios or provides redundancy in a critical input category.

The fifth stage is managerial review and decision governance. Procurement decisions in food systems have consequences for cost, safety, sustainability, continuity, and reputation. The final ranking should therefore be reviewed by a cross-functional procurement committee before implementation. The committee examines whether the analytical output is consistent with policy constraints, supplier contracts, food safety requirements, and risk appetite. This converts the analytics model into a decision-support system rather than an automated purchasing rule. Figure 2 emphasizes this system-level integration between data, judgment, scoring, and governance.

4. Data, Measurement, and Modeling Design

The empirical demonstration is based on an illustrative case of a medium-sized Malaysian food manufacturer that purchases processed agricultural ingredients for packaged food production. Six suppliers are evaluated by a panel of procurement, quality, sustainability, and logistics experts. To avoid over-identification with a single firm, the suppliers are anonymized as S1 to S6. The case is designed to reflect common procurement conditions in food manufacturing: suppliers differ in price, delivery reliability, audit transparency, environmental practices, and continuity capability. The objective is to select a primary supplier while identifying backup suppliers and improvement targets.

Table 1 reports the criteria used in the analysis. The criteria are deliberately organized into dimensions that reflect both business performance and societal responsibility. The economic dimension remains important because food manufacturers operate under tight margins and volatile input prices. However, environmental, social, and resilience criteria are given equal structural status in the framework. This prevents the decision model from reducing procurement to low-cost purchasing. The digital traceability dimension is included because food procurement increasingly depends on platform-based information exchange, audit trail completeness, and real-time documentation (Lu, 2019b; Lu, 2018; Xu et al., 2021; Chen et al., 2024).

Table 1. Sustainable-resilient food procurement criteria used in the analytical framework.

Dimension	Representative criteria	Data source	Managerial interpretation
Economic performance	Cost stability; quality reliability;	Quotes; invoices; non-	Determines whether supplier

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	delivery cost	conformance records	economics are sustainable beyond spot price
Environmental sustainability	Emissions; waste; packaging; resource efficiency	Audit records; packaging logs; supplier disclosures	Identifies ecological burden and green improvement potential
Social responsibility	Labor compliance; safety; ethical sourcing	CSR audits; third-party certificates; complaints	Protects legitimacy and reduces reputational exposure
Resilience capability	Continuity; flexibility; recovery speed; capacity buffer	Delivery history; disruption logs; recovery plans	Determines supplier reliability under disturbance
Digital traceability	Data sharing; platform integration; audit readiness	ERP logs; traceability files; digital certificates	Supports food safety, recall management, and accountability

The criteria structure deliberately combines measurable procurement data with expert assessment. This creates a common language for procurement, quality, logistics, and sustainability teams.

Expert judgments are collected using a five-level linguistic scale from very weak to very strong. Each linguistic term is mapped to an ordered uncertainty pair that contains support and concern. Table 2 provides the scale used in the demonstration. The scale allows experts to express asymmetric assessment. A criterion value can be high support and low concern, medium support and medium concern, or low support and high concern. This is especially useful for food procurement because supplier records often contain both positive and negative evidence. For instance, a supplier may have strong delivery history but weak environmental documentation.

Table 2. Linguistic supplier-evaluation scale and uncertainty-aware score representation.

Linguistic term	Support degree	Concern degree	Interpretation
Very strong	0.90	0.10	Highly reliable evidence of supplier performance
Strong	0.75	0.25	Positive evidence with limited concern
Moderate	0.55	0.45	Mixed or balanced evidence
Weak	0.35	0.65	Concern dominates positive evidence
Very weak	0.15	0.85	Serious performance or documentation weakness

Objective data are constructed from procurement records, audit summaries, quality non-conformance logs, delivery deviation rates, packaging waste records, complaint reports, and continuity risk indicators. Each criterion is standardized to a common direction so that higher values represent better performance. Missing values are handled through conservative imputation: if a supplier lacks verifiable documentation on a criterion, the corresponding score is reduced rather than estimated optimistically. This assumption reflects the managerial view that lack of evidence is itself a risk in food procurement.

Figure 3 shows the difference between subjective, objective, and combined criteria weights for the ten most influential criteria. Expert weights place relatively high importance on delivery continuity, recovery capability, labor compliance, and traceability. Objective weights place more emphasis on cost stability, emissions, and flexibility because these criteria display larger differences across suppliers in the performance matrix. The combined weights retain both perspectives and avoid dominance by a single information source. This result supports the view that procurement analytics should not replace expert judgment but should discipline and balance it with data (Akter et al., 2016; Gupta and George, 2016; Yu et al., 2018).

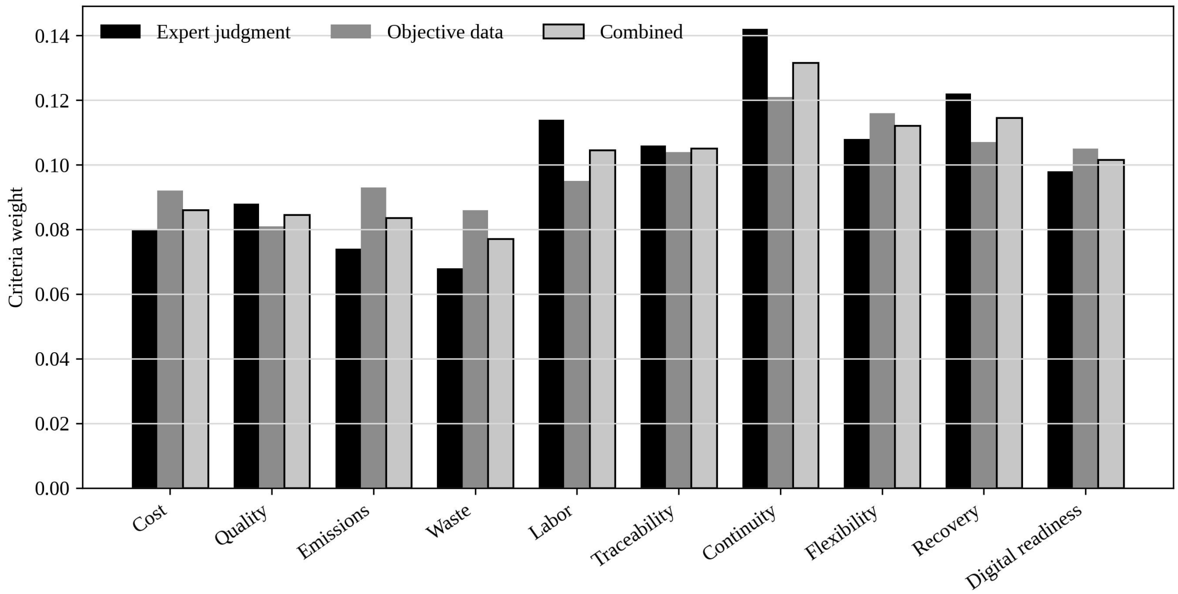

Figure 3. Comparison of expert judgment, objective data, and combined criteria weights.

The computational design uses four equations. First, linguistic evaluations are converted into uncertainty scores and aggregated across experts. Second, subjective and objective weights are combined by the α parameter. Third, supplier performance is normalized by multiple scaling rules to reduce dependence on any single normalization logic. Fourth, comprehensive scores are computed and ranked in descending order. Because the framework is designed for managerial use, the article emphasizes interpretability, sensitivity testing, and procurement implications instead of presenting an overly technical algorithmic derivation.

5. Results and Interpretation

Table 3 presents the combined criteria weights for the five main dimensions and selected sub-criteria. The resilience dimension obtains the highest aggregate weight, followed by social responsibility, environmental sustainability, economic performance, and digital traceability. This does not imply that cost is unimportant. It indicates that in a disruption-sensitive food procurement context, the difference between suppliers is no longer explained primarily by price. Delivery continuity, labor compliance, recovery capacity, safety records, and audit visibility become decisive because the cost of supplier failure can exceed the savings from low quoted prices.

At the sub-criteria level, continuity capability, labor safety compliance, recovery speed, quality reliability, and traceability completeness are among the most influential criteria. This finding is consistent with the idea that sustainable procurement should evaluate both the supplier's ordinary operating performance and its capacity to behave responsibly under stress. Supplier resilience is not simply a buffer capacity; it also reflects the institutional ability to communicate, document, recover, and collaborate during uncertainty (Pettit et al., 2010; Hohenstein et al., 2015; Kamalahmadi and Parast, 2016).

Table 3. Aggregated weights of the main evaluation dimensions and selected high-impact sub-criteria.

Dimension	Aggregate weight	High-impact sub-criteria	Interpretive implication
Resilience capability	0.268	Continuity, recovery, flexibility	Disruption response dominates supplier suitability
Social responsibility	0.214	Labor safety, ethical compliance	Social legitimacy is a key procurement risk
Environmental sustainability	0.192	Emissions, waste, packaging	Green performance differentiates strategic suppliers
Economic performance	0.178	Cost stability, quality reliability	Cost remains necessary but not sufficient
Digital traceability	0.148	Data sharing, audit readiness	Traceability supports recall and transparency

Table 4 reports the supplier ranking results. Supplier S1 obtains the highest comprehensive score, followed by S2 and S3. S1 performs strongly in continuity, quality reliability, labor compliance, and traceability completeness. S2 is competitive in cost and environmental performance but shows weaker recovery readiness. S3 shows acceptable economic and digital performance but weaker social responsibility indicators. S4, S5, and S6 have lower scores due to combinations of high delivery variability, incomplete documentation, and lower resilience capacity. Figure 4 visualizes the final comprehensive scores.

Table 4. Supplier ranking results under the combined analytics model.

Supplier	Comprehensive score	Rank	Strengths	Development requirement
S1	0.823	1	Continuity, quality, compliance	Maintain and monitor
S2	0.771	2	Cost and environmental practices	Recovery planning
S3	0.704	3	Digital readiness	Social compliance
S4	0.690	4	Packaging efficiency	Delivery variability
S5	0.642	5	Local proximity	Documentation completeness
S6	0.603	6	Low price	Audit and resilience capability

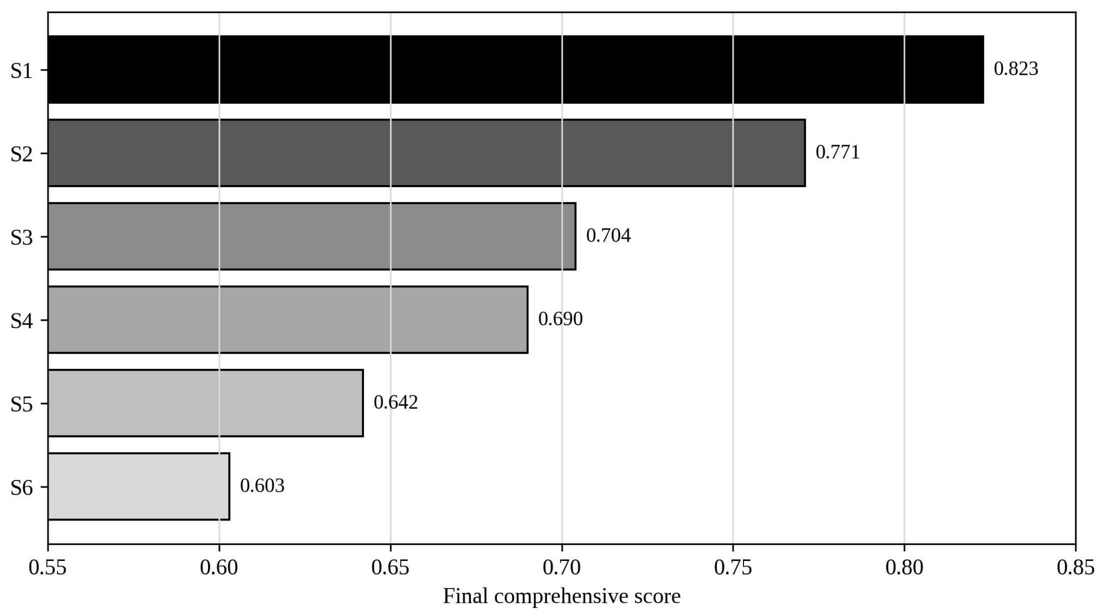

Figure 4. Final supplier ranking based on comprehensive sustainable-resilient procurement scores.

The ranking result has several managerial interpretations. First, S1 should be selected as the preferred supplier for the main sourcing allocation. Second, S2 should not be eliminated; it should

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be developed as a strategic secondary supplier because its environmental score is strong and its recovery weakness may be improved by joint planning. Third, S3 may be suitable for lower-risk procurement categories but should not be used for high-dependence inputs until its social compliance and continuity documentation are improved. Fourth, S4 to S6 require targeted development plans before they can be considered reliable suppliers for continuity-sensitive materials.

The supplier score decomposition also shows why the hybrid model is more informative than a simple weighted average. S1 does not dominate every criterion. It wins because it combines acceptable cost with high reliability, strong compliance, and resilience. S2 wins several economic and environmental criteria but loses ground in recovery and audit continuity. A purely cost-driven model would rank S2 higher, while a purely expert-driven model may overstate S1 if experts are influenced by recent delivery experience. The hybrid analytics framework makes the trade-off explicit and auditable.

From a business analytics perspective, the result demonstrates that supplier selection can be converted into a structured evidence system. Instead of asking whether a supplier is simply good or bad, the firm can ask which supplier is robust under the expected procurement strategy, which criteria drive ranking changes, and which supplier development investments would produce the greatest improvement. This shifts supplier selection from episodic evaluation to continuous procurement intelligence (Choi et al., 2018; Bag et al., 2020; Baryannis et al., 2019).

6. Robustness and Sensitivity Analysis

Robustness analysis is necessary because supplier selection under uncertainty should not depend on one arbitrary parameter setting. This study conducts three tests: α sensitivity, normalization sensitivity, and disruption scenario sensitivity. The α sensitivity analysis varies the balance between expert judgment and objective weighting from 0 to 1. Figure 5 shows that S1 remains the preferred supplier across the full α range. S2 remains the second-ranked supplier in most settings, although the distance between S1 and S2 narrows when α is close to 0, meaning when objective data dominate. This suggests that S1's advantage is not merely the product of expert preference.

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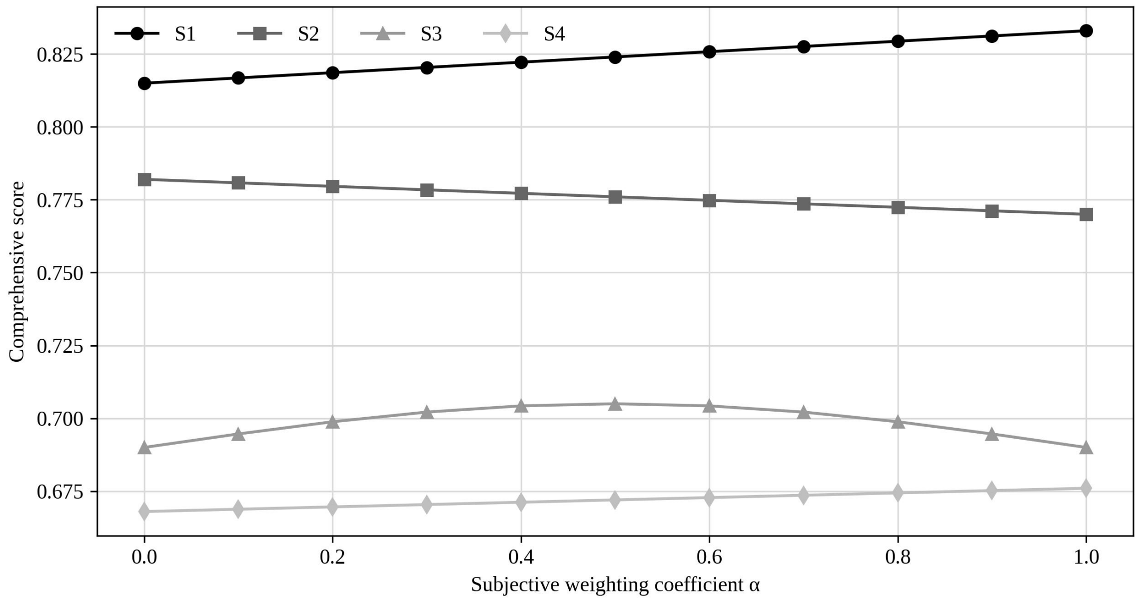

Figure 5. Sensitivity of supplier scores to the subjective-objective weighting coefficient.

Normalization sensitivity examines whether the ranking changes when the performance matrix is standardized by linear-sum, max-based, or max-min normalization. Table 5 reports that the first three suppliers remain stable in all tested settings. Lower-ranked suppliers show some movement because their weaknesses are concentrated in different criteria and respond more strongly to normalization rules. This is expected: when suppliers are close in overall performance and differ mainly in small risk indicators, ranking uncertainty increases. The managerial implication is that a procurement committee should not over-interpret small score differences among lower-ranked alternatives.

Table 5. Robustness of supplier ranking across normalization and disruption scenarios.

Scenario	Top supplier	Second supplier	Ranking stability	Managerial meaning
Base case	S1	S2	High	Use S1 as primary source
Objective-weight dominant	S1	S2	High	Ranking not driven by expert bias
Expert-weight dominant	S1	S2	High	Managerial judgment supports result
Transport disruption	S1	S3	Moderate	Increase resilience weight and backup capacity
Sustainability audit tightening	S1	S2	High	S2 remains a strong development candidate

Disruption scenario sensitivity tests how supplier ranking changes under three plausible stress conditions: transport disruption, sustainability audit tightening, and quality non-conformance shock. Under the transport disruption scenario, resilience and recovery criteria receive higher weights. S1 continues to rank first, while S2 loses score because its recovery capability is weaker. Under sustainability audit tightening, environmental and social documentation weights increase; S2 improves but does not overtake S1. Under quality non-conformance shock, quality reliability and traceability weights increase; S1’s lead widens. These scenarios support the conclusion that S1 is not merely the best supplier in normal conditions but also the most robust candidate across plausible stress contexts.

The robustness results have practical consequences for procurement policy. A firm should not

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use one fixed ranking as the sole basis for annual contracts. Instead, the final supplier portfolio should combine ranking, scenario stability, and improvement pathways. Supplier S1 is suitable for primary allocation. Supplier S2 should be retained as a backup and given resilience improvement targets. Supplier S3 should receive social compliance and continuity documentation requirements. Suppliers S4 to S6 may be used only for non-critical categories or subject to supplier development plans. This interpretation aligns with resilience research that emphasizes portfolio diversity, redundancy, and adaptive supplier relationships rather than static optimization (Christopher and Peck, 2004; Ponomarov and Holcomb, 2009; Ivanov and Dolgui, 2020).

The sensitivity analysis also demonstrates the importance of transparency. If a ranking changes substantially when α or normalization settings change, managers should treat the output as a discussion prompt rather than a final decision. If the ranking is stable across scenarios, managers can have greater confidence in the result. Thus, robustness testing becomes a governance device. It allows procurement teams to distinguish between strong analytical conclusions and fragile score artifacts. This is particularly important when supplier selection affects food safety, sustainability commitments, and continuity of production.

7. Discussion and Managerial Implications

The proposed framework has several managerial implications. First, food procurement teams should treat supplier selection as a data-governance process. The quality of the final ranking depends on the quality of audit records, delivery data, supplier disclosures, and expert assessment protocols. Data quality problems cannot be solved at the ranking stage. They must be addressed through standardized supplier data templates, documentation rules, and cross-functional review. This is consistent with supply chain analytics research showing that data quality is a prerequisite for predictive and decision analytics (Hazen et al., 2014; Schoenherr and Speier-Pero, 2015).

Second, supplier selection should include both sustainability and resilience. Firms sometimes separate sustainable sourcing programs from business continuity planning. This separation creates blind spots. A sustainable supplier that fails under disruption cannot support continuity, while a resilient supplier that ignores environmental or social responsibility may undermine long-term legitimacy. The framework therefore treats sustainability and resilience as complementary rather than competing objectives. This reflects the emerging view that supply chains must be simultaneously responsible, adaptive, and economically viable (Sarkis et al., 2011; Sarkis, 2012; Rao and Holt, 2005; Zhu et al., 2013).

Third, the model provides a practical way to manage expert disagreement. Procurement managers, quality professionals, logistics specialists, and sustainability officers often evaluate suppliers through different lenses. Expert disagreement should not be hidden. It should be represented explicitly and combined with objective data. Structured expert judgment allows decision-makers to express strategic priorities, while objective weighting prevents criteria with little discriminating power from receiving excessive influence. The hybrid weighting mechanism therefore functions as a negotiation instrument inside the procurement team.

Fourth, the framework can be embedded in a digital procurement dashboard. Figure 6 proposes a roadmap for moving from data readiness to continuous review. The roadmap begins with data readiness and criteria governance, proceeds to hybrid scoring and supplier portfolio

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design, and ends with continuous monitoring. This enables the firm to move from annual supplier audits to a living analytics system. With digital traceability, cloud services, IoT data, and blockchain-enabled records, procurement teams can update supplier performance scores more frequently and detect risk signals earlier (Lu and Xu, 2019; Lu et al., 2020; Lu and Ning, 2020; Chen et al., 2024).

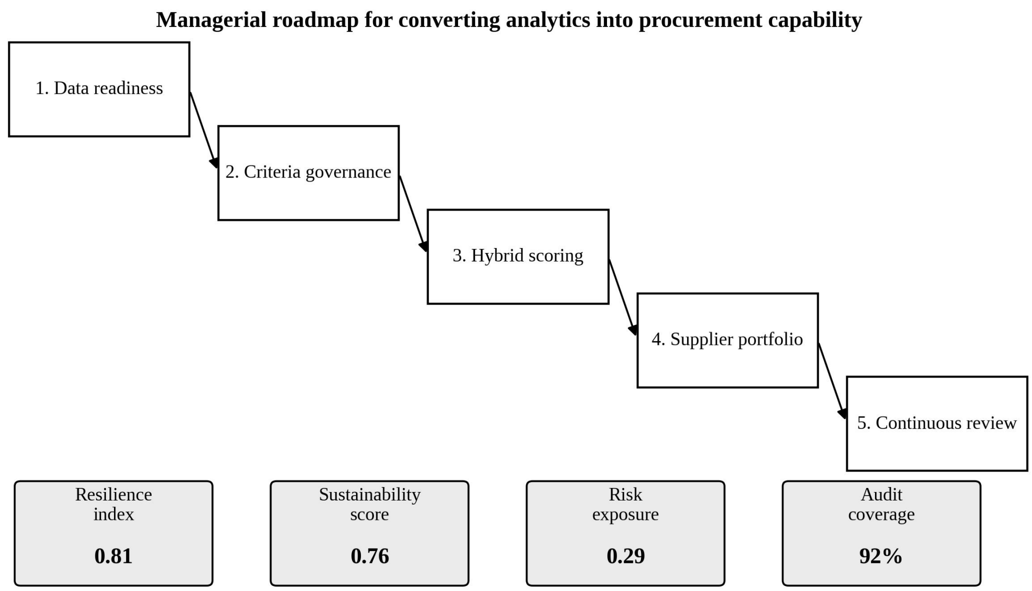

Figure 6. Managerial roadmap for converting supplier analytics into sustainable-resilient procurement capability.

Fifth, the framework supports supplier development. Ranking suppliers should not be equated with excluding suppliers. In many food supply chains, local suppliers may lack sophisticated documentation systems but provide strategic proximity and flexibility. Analytics can identify where development is needed: packaging documentation, food safety audit records, delivery recovery planning, labor compliance, or digital traceability. This aligns with sustainable supplier management research, which emphasizes supplier development and monitoring alongside initial selection (Zimmer et al., 2016; Luthra et al., 2017).

Finally, the framework has strategic relevance for food manufacturers facing volatile climate, geopolitical, and public health risks. Procurement choices influence not only input cost but also production continuity, carbon exposure, reputation, regulatory compliance, and customer trust. The proposed analytics system helps managers justify decisions with evidence and communicate the logic of supplier selection to internal stakeholders, auditors, and external partners. It turns supplier evaluation into an auditable management process rather than a discretionary purchasing decision.

Implementation should begin with a supplier data governance audit. Many food manufacturers already possess large amounts of useful procurement data, but the data are usually dispersed across purchasing modules, quality systems, warehouse records, sustainability questionnaires, and email-based supplier communications. The proposed framework requires a

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master supplier record that links these data sources through a common supplier identifier. Each criterion should be associated with a defined data owner, update frequency, validation rule, and documentation standard. For example, delivery continuity should be connected to purchase order fulfillment records, while social responsibility should be linked to audit certificates and corrective-action logs. When this governance layer is absent, supplier analytics can create a false sense of precision. When it is present, the framework becomes a practical infrastructure for evidence-based procurement rather than a purely mathematical scoring exercise (Hazen et al., 2014; Yu et al., 2018; Lu et al., 2024b).

The framework also changes how supplier development programs are designed. Conventional supplier development often focuses on broad improvement themes, such as cost reduction or quality improvement. The proposed analytics model allows development programs to become more targeted. If a supplier loses ranking points mainly because of weak recovery capability, the appropriate intervention is not a price negotiation but a continuity plan, backup logistics agreement, or shared safety-stock arrangement. If a supplier loses points because of traceability gaps, the firm can require digital documentation, batch-level records, and platform integration. If the weakness is labor compliance, the intervention must involve third-party audit, code-of-conduct training, and corrective-action verification. In this sense, ranking becomes the starting point of supplier improvement and not the end of the purchasing process (Zimmer et al., 2016; Luthra et al., 2017; Sarkis, 2012).

For senior managers, the framework provides a governance language that connects procurement analytics with corporate strategy. The supplier portfolio can be reported through four indicators: sustainability score, resilience index, traceability readiness, and procurement risk exposure. These indicators allow executives to evaluate whether procurement policy is aligned with sustainability commitments, continuity requirements, food safety obligations, and customer expectations. This is particularly important when firms face external pressure from regulators, retailers, auditors, and consumers. A transparent supplier analytics system can support public reporting, ESG governance, and internal accountability. It can also reduce conflicts between departments because procurement, quality, sustainability, and logistics teams can discuss the same evidence base rather than relying on disconnected scorecards (Carter and Rogers, 2008; Pagell and Wu, 2009; Bag et al., 2020).

The digital extension of the framework is equally important. Future food procurement platforms can embed the hybrid model within ERP systems, supplier portals, blockchain traceability infrastructures, and IoT-enabled logistics monitoring. In such a setting, supplier scores need not be recalculated only during annual review. They can be updated when a supplier misses delivery windows, submits new audit evidence, changes packaging practices, or records a food safety incident. The analytics engine can then trigger alerts, recommend supplier development actions, or escalate high-risk suppliers for manual review. This real-time extension is consistent with the broader transition toward digital supply chains, cyber-physical industrial systems, and trusted data sharing infrastructures (Büyüközkan and Göçer, 2018; Lu, 2017a; Lu and Xu, 2019; Chen et al., 2024).

8. Conclusion

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This article proposed a business data analytics framework for sustainable and resilient food procurement under uncertainty. Building on uncertainty-aware multi-criteria decision logic, the framework integrates expert judgment and objective weighting to evaluate suppliers across economic, environmental, social, resilience, and digital traceability criteria. The case demonstration shows that a supplier ranking can be made more robust, interpretable, and managerially actionable when linguistic assessments, operational data, hybrid weighting, and sensitivity analysis are connected within a single decision-support architecture.

The findings indicate that the best procurement decision is not necessarily the lowest-cost supplier. In the illustrative food manufacturing case, the preferred supplier achieves the strongest overall performance because it combines competitive quality, delivery continuity, social compliance, recovery capacity, and traceability completeness. The result remains stable across weighting and scenario variations, suggesting that robust supplier selection depends on consistency across multiple decision views rather than dominance in a single criterion. This is important for food supply chains, where disruptions, sustainability risks, and safety failures can quickly generate operational and reputational damage.

The article makes three theoretical contributions. First, it reframes supplier selection as a business analytics system rather than a standalone ranking exercise. Second, it demonstrates how subjective and objective weighting can be combined under uncertainty to balance managerial priorities and data-driven information. Third, it connects supplier ranking with governance, sensitivity analysis, and supplier development. These contributions extend the link between management analytics and sustainable supply chain decision-making (Lu et al., 2024a; Lu et al., 2024b).

Several limitations remain. The empirical demonstration is illustrative and should be validated with larger multi-firm datasets. The criteria hierarchy may require adaptation for different food categories such as dairy, seafood, fresh produce, processed grains, or frozen products. Future research can integrate the proposed supplier score with order allocation, contract design, carbon pricing, inventory buffering, and multi-period sourcing. Future studies may also connect the framework with real-time digital twin dashboards, blockchain traceability records, and AI-based disruption prediction, thereby expanding the model from supplier selection to continuous procurement intelligence.

Overall, sustainable and resilient food procurement requires both analytical rigor and managerial judgment. The proposed framework provides a practical route for connecting these two requirements. By integrating expert knowledge, objective data, fuzzy uncertainty representation, robust ranking, and governance review, food manufacturers can make procurement decisions that are more transparent, resilient, and aligned with long-term sustainability goals.

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Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Nurul Aisyah Rahman: conceptualization, methodology, writing—original draft. Mohd Farid Azman: data analytics design, supplier criteria modeling, validation. Siti Norhayati Salleh: literature review, sustainability interpretation, table preparation. Ahmad Zulkifli Ismail: supervision, framework design, writing—review and editing.

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