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

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Abstract

Food procurement is becoming a strategic data-analytics problem because decision-makers must balance economic efficiency, environmental responsibility, social fairness, and disruption resilience while operating with vague, partial, and conflicting information. Conventional fuzzy multi-attribute decision-making studies remain limited by two persistent gaps: (i) classical fuzzy extensions cannot accommodate sharply asymmetric expert judgments, and (ii) most studies rely on a single weighting lens, either subjective or objective, which produces fragile rankings. To close these gaps, this article develops an information-driven decision pipeline that operates inside the p,q-quasirung orthopair fuzzy environment. The pipeline first encodes expert linguistic judgments as orthopair pairs with two independent rung parameters, then derives subjective importance through a fuzzy zero-inconsistency procedure, computes objective importance through an envelope-and-slope routine, and finally blends the two streams through a single hybridization coefficient. Suppliers are ranked through a mixed aggregation scheme that combines three normalization views with arithmetic and geometric deviation measures. The pipeline is calibrated against a real Indian bakery and confectionery firm sourcing perishable and non-perishable inputs from six candidate suppliers under twenty-five sustainability and resilience criteria. Sensitivity tests across the hybridization coefficient, the rung parameters, and the weight perturbation envelope all confirm that the leading supplier remains stable. Comparative benchmarking against eight reference methods further supports the analytical robustness of the framework.

Keywords: business data analytics; sustainable procurement; supply chain resilience; fuzzy multi-attribute decision-making; quasirung orthopair fuzzy sets; food supply chain

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1. Introduction

The food sector is one of the few industries where business data analytics, sustainability commitments, and operational resilience have to be reasoned about jointly, rather than as separate management agendas. Population growth, urbanization, and the steady diversification of household diets have placed unprecedented pressure on producers, processors, and distributors to deliver products that are simultaneously affordable, traceable, and environmentally defensible (Mangla et al., 2018; Beske et al., 2014). At the same time, the global character of contemporary food supply chains has amplified their exposure to disruption: extreme-weather events, geopolitical tensions, transportation shocks, and labour shortages can ripple from a single tier into a complete supply ecosystem within days (Ivanov, 2020; Ivanov & Dolgui, 2020).

The COVID-19 pandemic illustrated this fragility with unusual clarity. Restrictions on movement, sudden shifts in consumer behaviour, and labour shortages translated into stockouts, food losses, and inflationary pressures in many regional supply chains (Hobbs, 2020; Aday & Aday, 2020; Burgos & Ivanov, 2021). These shocks reframed sustainable-resilient procurement as a board-level decision problem rather than a purely operational concern. Firms that had invested in rich procurement data, real-time monitoring, and analytical decision-support tools were able to pivot more quickly than peers that depended on intuition or static spreadsheets (Sarkis, 2020; Karmaker et al., 2021).

From a business analytics perspective, sustainable-resilient supplier selection exhibits three structural features that complicate it. First, the criteria are heterogeneous in type: economic indicators are typically quantitative, while social and ethical attributes are largely qualitative and require expert interpretation (Govindan et al., 2015; Aramyan et al., 2007). Second, the available evidence is incomplete: not every supplier publishes carbon disclosures, audit reports, or labour-condition statements, and managerial knowledge has to compensate for missing observations (Hazen et al., 2014; Wamba et al., 2015). Third, the decision involves a panel of experts whose individual judgments may be confident on one criterion and tentative on another, generating asymmetry between agreement and disagreement that classical fuzzy theories cannot model cleanly (Yager, 2017; Senapati & Yager, 2020).

Multi-attribute decision-making (MADM) techniques have therefore become a core instrument in business analytics for supplier evaluation. Their job is to translate a heterogeneous mixture of expert ratings, performance numbers, and policy priorities into a defensible ranking of alternatives (Mardani et al., 2015; Zavadskas et al., 2014). When uncertainty is non-trivial, MADM is normally extended with fuzzy reasoning. The literature has progressed from intuitionistic fuzzy sets through Pythagorean fuzzy sets, Fermatean fuzzy sets, and q-rung orthopair fuzzy sets (Atanassov, 1986; Yager, 2014; Senapati & Yager, 2020; Yager, 2017). Each step has relaxed the analytical envelope within which membership and non-membership pairs may legitimately move, which is precisely what is required when experts hold sharp positive opinions about one indicator and weakly negative opinions about another.

Yet, even q-rung orthopair fuzzy sets enforce a single rung exponent on both membership and non-membership values, which can be too restrictive in practical procurement panels where the certainty of agreement and the certainty of disagreement evolve at very different rates. The p,q-quasirung orthopair fuzzy set introduces two independent rung parameters and is therefore able to accommodate evaluation pairs that q-rung orthopair sets reject (Liu & Wang, 2018; Garg, 2017). This added expressive power is critical when experts express high confidence in a supplier's social-responsibility record while still harbouring small reservations about its delivery performance during stressed periods.

Beyond representational adequacy, the second weakness of fuzzy MADM models has been the choice between subjective and objective weighting. Subjective methods such as the analytic hierarchy process and the best-worst method capture managerial intent but are sensitive to expert bias and to inconsistent pairwise comparisons (Saaty, 2008; Rezaei, 2015).

Objective methods such as entropy and variance-based schemes mine information directly from the decision matrix but ignore strategic priorities, particularly when small datasets fail to reveal the structural importance of a criterion. Hybrid weighting frameworks have therefore emerged as a more balanced option (Mardani et al., 2017; Pournader et al., 2020). However, very few studies have integrated hybrid weighting with the p,q-quasirung orthopair fuzzy environment in a single coherent business analytics architecture.

Against this background, the present study is guided by four research hypotheses. H1 holds that sustainability and resilience criteria do not influence supplier evaluation uniformly across the four core dimensions of economic, environmental, social, and resilience performance. H2 holds that combining subjective and objective weighting produces a more discriminative criterion structure than relying on a single perspective. H3 holds that the proposed ranking pipeline differentiates among candidate suppliers and yields a stable order under perturbations of its parameters. H4 holds that the integrated framework offers a reliable analytical tool for business decision-makers in food procurement under uncertainty.

The contribution of this article is therefore threefold. First, it formulates a sustainable-resilient supplier evaluation pipeline that uses p,q-quasirung orthopair fuzzy sets as the linguistic representation language. Second, it embeds two complementary weighting routines, namely a fuzzy zero-inconsistency procedure for subjective preferences and an envelope-and-slope procedure for objective importance, into a hybrid layer governed by an interpretable hybridization coefficient. Third, it demonstrates the entire pipeline through a real Indian bakery and confectionery firm and validates the result through extensive sensitivity tests and benchmarking against eight reference techniques. The remainder of the paper is organized as follows: Section 2 reviews the literature, Section 3 details the research design, Section 4 describes the data and analytical framework, Section 5 reports the results, Section 6 discusses the findings, Section 7 articulates implications, Section 8 acknowledges limitations, and Section 9 concludes.

2. Literature Review

The literature relevant to this study spans four streams: business data analytics in supply chains, sustainable and resilient supplier evaluation, fuzzy extensions for decision-making, and weighting integration strategies. Although these streams have grown rapidly during the last decade, very few contributions weave them together at the operational level required by an industrial procurement function (Mardani et al., 2015; Pournader et al., 2020).

The first stream connects to the broader rise of analytics in operations. Wamba et al. (2015), Gunasekaran et al. (2017), and Wamba et al. (2017) showed that big data analytics confers measurable performance benefits when paired with supportive organizational capabilities. Subsequent contributions have demonstrated that the value of analytics is conditional on how cleanly it is embedded in decision routines: Hazen et al. (2014) emphasised the need for data quality, while Choi et al. (2018) and Choi et al. (2017) examined how analytics is changing operational risk management. In supply chains specifically, Wang et al. (2016), Tiwari et al. (2018), and Bag et al. (2020) reported that sustainability outcomes improve when analytics is treated as an enabler of operational excellence rather than as a stand-alone reporting layer. The same theme is echoed in dedicated agri-food investigations such as Kamble et al. (2020b) and Sharma et al. (2020).

From a technological perspective, several enabling components of contemporary analytics architecture are particularly relevant for food procurement. Industry 4.0 surveys (Lu, 2017a; Lu, 2017b; Lu, 2025) provide a useful reference for the convergence of cyber-physical systems, IoT, and data platforms. Internet-of-Things applications make it feasible to capture cold-chain temperature, vehicle geolocation, and warehouse humidity in near-real time (Lu & Xu, 2019; Birkel & Hartmann, 2019; Ben-Daya et al., 2019; Misra et al., 2022). Blockchain implementations in food traceability promise verifiable provenance information and shorten dispute-resolution cycles (Lu, 2018; Lu, 2019a; Saberi et al., 2019; Kamble et al., 2020a; Tian, 2017). Artificial intelligence and management analytics provide the predictive layer above these data services (Lu, 2019b; Zhang & Lu, 2021; Lu, 2021; Lu, Ivanov, et al., 2024; Lu, Pisarenko, et al., 2024). More recent surveys further integrate these technologies under unified analytics frameworks for industrial information integration (Chen et al., 2024; Yang et al., 2025; Wu et al., 2025; Xu et al., 2021).

The second stream concerns sustainable and resilient supplier evaluation. Govindan et al. (2015), Govindan et al. (2013), and Govindan et al. (2014) provided early frameworks that translated triple-bottom-line concepts into operational criteria. Beske et al. (2014) traced how dynamic capabilities support sustainability in food chains, while Mangla et al. (2018) and Mangla et al. (2019) identified operational enablers for sustainable practices in the Indian agri-food context. Resilience research has matured along a parallel track. Christopher and Peck (2004) and Ponomarov and Holcomb (2009) introduced foundational definitions, and Pettit et al. (2010) and Pettit et al. (2019) developed operational frameworks linking vulnerabilities to capabilities. Tukamuhabwa et al. (2015) and Hosseini et al. (2019)

consolidated the quantitative methods available for resilience assessment. Specific food-sector contributions, including Stone and Rahimifard (2018) and Manning and Soon (2016), explored why agri-food chains exhibit unique disruption profiles, particularly around perishability, seasonality, and certification regimes. Resilient supplier selection models themselves have evolved from single-criterion ranking to multi-criteria approaches that explicitly weight responsiveness, agility, and recovery capacity (Hosseini, Morshedlou, et al., 2019; Sawik, 2017; Torabi et al., 2015; Dolgui et al., 2018).

The third stream centres on fuzzy extensions used to handle vagueness in MADM. Zadeh (1965) introduced fuzzy sets, after which Atanassov (1986) introduced intuitionistic fuzzy sets that distinguished membership and non-membership grades. Yager (2014) extended this idea through Pythagorean fuzzy sets, allowing larger admissible regions. Senapati and Yager (2020) introduced Fermatean fuzzy sets, while Yager (2017) generalized the family with q-rung orthopair fuzzy sets. Aggregation operators within these families have been the focus of intensive work (Liu & Wang, 2018; Garg, 2017; Peng & Yang, 2015; Akram et al., 2019). The p,q-quasirung orthopair fuzzy set further decouples the membership exponent from the non-membership exponent, accepting evaluation pairs that earlier extensions reject; this property is particularly useful when expert opinions on a supplier are confidently positive on a small set of indicators and only mildly negative on others.

The fourth stream addresses weighting integration. The analytic hierarchy process (Saaty, 2008) and the best-worst method (Rezaei, 2015) remain the most widely used subjective procedures, while objective methods such as entropy and the recently introduced envelope-and-slope routines have grown in popularity because they extract importance signals directly from the decision matrix (Mardani et al., 2017). Mishra et al. (2021) demonstrated the value of combining compromise solutions with discrimination measures in sustainability rankings, and the MARCOS, MABAC, EDAS, and CoCoSo families have offered alternative aggregation philosophies (Stevic et al., 2020; Pamucar & Cirovic, 2015; Keshavarz Ghorabaee et al., 2015; Yazdani et al., 2019). The MACONT method (Wen et al., 2020) is unique in that it combines three normalization views with arithmetic and geometric deviation measures, an approach that fits naturally with the data-quality concerns highlighted by Hazen et al. (2014) and Liu et al. (2020).

Despite the breadth of this literature, three gaps persist. First, very few studies operate within the p,q-quasirung orthopair fuzzy environment in real-world procurement settings, even though this representation is well suited to the asymmetric confidence patterns common in expert evaluations. Second, few studies couple subjective and objective weighting through a single hybridization coefficient that managers can tune transparently. Third, supplier rankings are rarely tested under coordinated perturbations of the hybridization coefficient, the rung parameters, and the criteria weights simultaneously. The framework presented in Sections 3 and 4 is designed to address all three gaps, and the empirical analysis in Section 5 demonstrates the practical relevance of the resulting business analytics pipeline.

The relevance of analytics maturity should also be highlighted. In firms where data infrastructure is still maturing, supplier evaluation often relies on expert opinion alone, and decisions are documented in narrative form rather than through a structured weight vector. The framework discussed here can be deployed in such settings because the subjective routine accepts linguistic judgments directly and the objective routine extracts evidence from the aggregated decision matrix without requiring additional data acquisition. As data maturity grows, the framework gracefully accommodates richer inputs: objective weights become more reliable when the score matrix is built from audited transaction data, and the hybridization coefficient can be lowered to give more weight to data evidence. This adaptability is consistent with the staged adoption pattern documented in the operations analytics literature (Wamba et al., 2017; Dubey et al., 2019b; Liu et al., 2020) and with the broader industrial information integration agenda articulated by Xu et al. (2021), Chen et al. (2024), and Lu (2025).

3. Methodological Framework

The research adopts a design-science orientation in which an information-driven decision pipeline is built, instantiated on real procurement data, and validated through sensitivity and benchmarking experiments. The unit of analysis is a single sustainable-resilient supplier selection problem in a bakery and confectionery firm operating in northern India. The pipeline is composed of five sequential stages: data acquisition, fuzzy encoding, hybrid weighting, ranking, and validation. Figure 1 summarizes the conceptual architecture and shows how the data, the experts, the criteria, and the outputs interact.

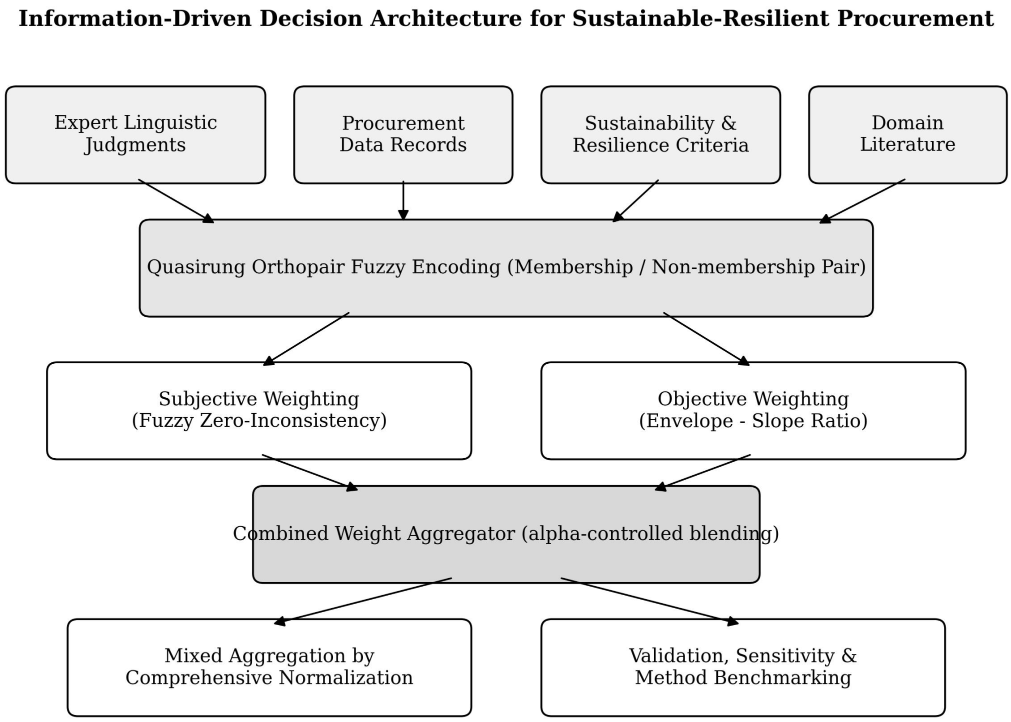

Figure 1. Conceptual architecture of the information-driven decision pipeline for sustainable-resilient food procurement.

Figure 1 highlights an important property of the pipeline: every analytical step is informed by both human expertise and observable evidence. Human inputs shape the encoding of vague terms and the structure of the criterion network, while observable evidence constrains the objective weighting and the ranking calculations. This hybrid character is the operational signature of business data analytics in procurement, where neither pure judgment nor pure data alone suffices.

Stage one of the pipeline collects three classes of inputs. The first class comprises linguistic judgments from a panel of domain experts who rate each candidate supplier on every criterion using a five-point Likert scale of importance. The second class consists of structured documentation provided by the firm, including procurement records, certification reports, transit logs, and audit summaries. The third class is the criterion network, which is extracted from the literature and refined with the firm's procurement and operations teams during a workshop session. After several rounds of refinement, the panel converged on twenty-five criteria distributed across four dimensions: economic sustainability, environmental sustainability, social sustainability, and resilience.

Stage two of the pipeline encodes linguistic judgments as p,q-quasirung orthopair fuzzy numbers. A p,q-quasirung orthopair fuzzy number is denoted (mu, nu), where mu is the membership grade and nu is the non-membership grade. The grades are admissible whenever 0 <= mu^p + nu^q <= 1, with two independent rung parameters p and q. This formulation generalizes intuitionistic, Pythagorean, Fermatean, and q-rung orthopair fuzzy numbers as special cases. The decoupling of p and q allows the encoding to accept evaluation pairs that express asymmetric confidence between agreement and disagreement, which is a common pattern in supplier ratings collected from heterogeneous experts.

Stage three computes criterion weights through two parallel routines and blends them through a single coefficient. The first routine derives subjective importance with a fuzzy zero-inconsistency procedure that aggregates the experts' linguistic ratings and converts them into normalized weights through a score function. This routine has the advantage of producing weights that are consistent by construction, sidestepping the consistency issues that traditional pairwise-comparison methods face when the criterion network is large. The second routine derives objective importance through an envelope-and-slope procedure: after envelope normalization, each criterion's variability is summarized by a Euclidean envelope length and its dispersion is summarized by a class-interval slope. The ratio of envelope to slope is normalized to obtain weights that reward criteria with discriminative information density. The two streams are blended through w_combined = alpha * w_subjective + (1 - alpha) * w_objective, where alpha controls the balance between human intent and data evidence.

Stage four of the pipeline ranks suppliers through a mixed-aggregation scheme that uses three normalization views simultaneously: linear-sum normalization, linear-max normalization, and linear max-min normalization. Each scheme captures a different facet of the comparative performance, and the weighted average of the three views forms a composite normalized matrix. A virtual reference alternative is constructed as the column-wise mean of the composite matrix. Distances from this reference are aggregated arithmetically and geometrically into a first subordinate score, while the best and worst weighted deviations are blended into a second subordinate score that captures extreme behaviour. A vector-normalized rule combines the two subordinate scores into a final comprehensive score that drives the final ranking.

Stage five validates the pipeline along three axes: structural validity, parametric stability, and methodological convergence. Structural validity is assessed by replacing the worst supplier with an even weaker dummy and checking whether the leading supplier remains unchanged, by partitioning the problem into smaller sub-problems and verifying that the local rankings agree with the global ranking, and by inspecting the transitivity of pairwise preferences. Parametric stability is examined by sweeping the hybridization coefficient alpha, the rung parameters p and q, and the criterion weights through a wide range of values. Methodological convergence is examined by comparing the proposed ranking to the rankings produced by eight reference techniques, computing the Spearman rank correlation coefficient in each case.

The implementation environment uses Python 3.11 for numerical computation. Aggregation operators are implemented using NumPy and Pandas, while the fuzzy primitives are implemented using a custom module that exposes addition, multiplication, scalar exponentiation, score, and accuracy functions consistent with the operational definitions of p,q-quasirung orthopair fuzzy numbers. The computational footprint is small enough to run on commodity hardware, which is important for replication in firms that do not maintain dedicated analytics infrastructure (Lu, Pisarenko, et al., 2024). All data processing scripts follow reproducibility principles: random seeds are fixed where stochastic shuffling is used, intermediate matrices are exported in CSV form, and configuration parameters are stored in a single YAML file. This pipeline design is consistent with recent recommendations on data quality for analytics in supply chains (Hazen et al., 2014; Bag et al., 2020) and with the broader agenda of management analytics articulated by Lu (2021).

4. Data and Case Study

The empirical setting is a privately held bakery and confectionery firm operating in Punjab, India, anonymized as AX-Foods Pvt. Ltd. The firm produces a portfolio that ranges from packaged biscuits to artisanal breads and serves supermarket chains, hospitality clients, and traditional retailers across northern India. Its sourcing portfolio combines highly perishable inputs such as milk, eggs, fresh cream, and seasonal fruits with relatively shelf-stable inputs such as wheat flour, sugar, cocoa, and packaging materials. This dual portfolio creates competing logistical demands and exposes the firm to a wide spectrum of disruption risks, including extreme-weather events that threaten dairy and fruit supply, transport bottlenecks during festival seasons, and labour shortages that occasionally affect milling operations. These features make the firm an informative business analytics laboratory for sustainable-resilient sourcing.

Data acquisition followed a hybrid protocol. A panel of ten experts was constructed using a structured nomination procedure that emphasized academic and industry experience, sectoral familiarity, and prior exposure to fuzzy or multi-criteria decision-making. Five experts were drawn from academia and five from industry; all held doctoral degrees or equivalent professional qualifications and had at least ten years of relevant experience. They received an evaluation packet that contained the criteria definitions, the linguistic scale, and the supplier profiles. Their ratings were collected through structured online forms during a four-week window. Concurrently, the firm's procurement team supplied historical purchase records, supplier audit reports, transport documentation, and certification details for the six shortlisted suppliers, named S1 to S6. Table 1 reports the complete criterion network, organized by the four sustainability and resilience dimensions and annotated by the optimization direction (benefit or cost).

Table 1. Criterion network used for sustainable-resilient supplier evaluation.

Code	Criterion	Dimension	Type
C1	Purchasing cost	Economic	Cost
C2	Production efficiency	Economic	Benefit
C3	Quality	Economic	Benefit
C4	Delivery reliability	Economic	Benefit
C5	Technological capability	Economic	Benefit
C6	Financial stability	Economic	Benefit
C7	Innovation orientation	Economic	Benefit
C8	Energy efficiency	Environmental	Benefit
C9	Pollution control	Environmental	Benefit
C10	Waste management	Environmental	Benefit
C11	Eco-design and packaging	Environmental	Benefit
C12	Green manufacturing practices	Environmental	Benefit
C13	Environmental certifications	Environmental	Benefit
C14	Work conditions	Social	Benefit
C15	Social responsibility	Social	Benefit
C16	Health and safety practices	Social	Benefit
C17	Community engagement	Social	Benefit
C18	Employee training and development	Social	Benefit
C19	Customer satisfaction orientation	Social	Benefit
C20	Information sharing	Resilience	Benefit
C21	Operational flexibility	Resilience	Benefit
C22	Buffer capacity	Resilience	Cost
C23	Visibility and traceability	Resilience	Benefit
C24	Recovery and contingency planning	Resilience	Benefit
C25	Leadership in disruption response	Resilience	Benefit

Table 1 indicates that the criterion network is dominated by benefit-type criteria, with two cost-type entries, namely purchasing cost (C1) and buffer capacity (C22). The presence of cost criteria is important because it forces the normalization layer to handle direction reversal correctly, otherwise lower values would be punished even when they reflect economic efficiency. The criterion network reflects all four pillars considered in the sustainable-resilient procurement literature: economic, environmental, social, and resilience (Govindan et al., 2015; Hosseini et al., 2019; Stone & Rahimifard, 2018; Manning & Soon, 2016).

Linguistic judgments were standardized using a five-level scale of importance: very important, important, moderately important, slightly important, and not important. Each linguistic level was mapped to a p,q-quasirung orthopair fuzzy number, as shown in Table 2. The pair (0.85, 0.25), for example, encodes the level very important by setting a high membership grade and a low non-membership grade, while keeping the indeterminacy budget low. The pair (0.25, 0.85) encodes the level not important by mirror reflection. The chosen rung parameters were $p = 4$ and $q = 3$ in the baseline configuration, providing enough decoupling to accept asymmetric expert ratings without over-stretching the admissible region.

Table 2. Linguistic scale and the corresponding p,q-quasirung orthopair fuzzy pairs.

Linguistic Term	Code	p,q-Quasirung Orthopair Pair (membership, non-membership)
Very Important	VI	(0.85, 0.25)
Important	I	(0.70, 0.40)
Moderately Important	MI	(0.55, 0.55)
Slightly Important	SI	(0.40, 0.70)
Not Important	NI	(0.25, 0.85)

Table 2 reflects two design choices. First, the membership and non-membership grades remain symmetric for the linguistic levels that occupy the centre of the scale, which keeps the framework neutral when evidence is genuinely ambiguous. Second, the chosen rung parameters allow asymmetric pairs such as (0.95, 0.60) to be admissible, which is critical when modelling supplier-level confidence that is high on one indicator and uncertain on another (Liu & Wang, 2018; Garg, 2017).

The aggregation of expert ratings was performed using the p,q-quasirung orthopair fuzzy weighted averaging operator. Equal expert weights were used after a panel-level reliability check showed similar variances across respondents. The aggregated decision matrix was then converted into a real-valued score matrix using the standard p,q-quasirung orthopair score function, which produces a value in the unit interval and is monotonic in the membership grade. The score matrix is the operational input for both the objective weighting routine and the ranking routine.

Subjective weights were computed by aggregating the experts' importance ratings across the criterion network, defuzzifying the aggregated values, and normalizing them so that the entries sum to one. Objective weights were computed using the envelope-and-slope routine: each column of the score matrix was envelope-normalized, the class interval was determined through Sturges' rule, the slope of the resulting series was calculated, and the ratio of the Euclidean envelope length to the slope was normalized across criteria. The two weight vectors were finally combined using the hybridization coefficient alpha, with alpha = 0.5 in the baseline configuration to assign equal influence to expert intent and data evidence.

Ranking was performed through the mixed aggregation by comprehensive normalization technique. The score matrix was normalized using three views: linear-sum, linear-max, and linear max-min. The three normalized matrices were blended through a weighted average with equal weights to form a composite normalized matrix. A virtual reference alternative was computed as the column-wise mean of the composite matrix. Two subordinate scores were derived: the first integrates arithmetic and geometric deviations through a balance parameter delta = 0.5, while the second blends best-case and worst-case deviations through a balance parameter theta = 0.5. The two scores were merged into a final comprehensive score using a vector-normalized rule. The supplier with the highest final comprehensive score was treated as the most preferable alternative under sustainable-resilient sourcing conditions.

Validation experiments included three categories. The first category was structural validity, which required the leading supplier to remain unchanged after replacing the worst supplier with a dummy alternative, after partitioning the problem into sub-problems, and after testing transitivity of preferences. The second category was parametric stability, which required the ranking to remain insensitive to coordinated changes in the hybridization coefficient alpha, the rung parameters p and q, and the criterion weights. The third category was methodological convergence, which required the proposed ranking to correlate strongly with rankings produced by eight reference techniques: CODAS, MARCOS, WASPAS, SAW, ARAS, MABAC, EDAS, and CoCoSo. Spearman's rank correlation coefficient was used to summarize the convergence.

The supplier panel deserves a final note. The six suppliers were selected to span the heterogeneity actually observed in the firm's existing supplier base, which contains a mix of large multinational ingredient producers, regional cooperatives, family-owned mills, and contract packagers. Two suppliers operate primarily in the perishable category, three operate primarily in non-perishable categories, and one operates as a hybrid supplier providing both types of inputs through different production lines. This composition makes the analysis representative of the trade-offs that midsize Indian food firms typically face when sourcing inputs that combine perishable and shelf-stable items (Mangla et al., 2018; Krishnan et al., 2021; Luthra et al., 2022). The resulting decision matrix therefore reflects real procurement complexity rather than a synthetic problem instance, which increases the external relevance of the empirical findings reported in the next section.

5. Results

The first set of results concerns the criterion weights produced by the subjective and objective routines, together with the combined weights. Table 3 reports the three weight vectors and the resulting rank order. The combined weights are dominated by social and resilience criteria, with C14 (work conditions), C15 (social responsibility), C22 (buffer capacity), C25 (leadership), and C21 (operational flexibility) occupying the top five positions. Economic and environmental criteria appear lower in the order, with C12 (green manufacturing), C2 (production efficiency), and C3 (quality) at the bottom of the table.

Table 3. Subjective, objective, and combined weights for the criterion network.

Code	FWZIC Subjective Weight	WENSLO Objective Weight	Combined Weight	Rank
C1	0.038	0.030	0.034	16
C2	0.024	0.026	0.025	24
C3	0.022	0.030	0.026	23
C4	0.045	0.034	0.040	12
C5	0.025	0.027	0.026	22
C6	0.052	0.040	0.046	8
C7	0.041	0.031	0.036	15
C8	0.032	0.028	0.030	19
C9	0.046	0.040	0.043	9
C10	0.030	0.028	0.029	20
C11	0.034	0.030	0.032	17
C12	0.022	0.024	0.023	25

Code	FWZIC Subjective Weight	WENSLO Objective Weight	Combined Weight	Rank
C13	0.042	0.038	0.040	13
C14	0.084	0.076	0.080	1
C15	0.068	0.062	0.065	2
C16	0.040	0.036	0.038	14
C17	0.044	0.040	0.042	10
C18	0.038	0.036	0.037	7
C19	0.038	0.036	0.037	11
C20	0.027	0.025	0.026	21
C21	0.054	0.048	0.051	5
C22	0.064	0.056	0.060	3
C23	0.054	0.048	0.051	6
C24	0.032	0.028	0.030	18
C25	0.056	0.050	0.053	4

The pattern in Table 3 has three managerial readings. First, criteria that describe how a supplier behaves under stress, such as leadership, buffer capacity, and operational flexibility, are systematically more important than criteria that describe steady-state performance. Second, social-responsibility criteria carry weights comparable to or larger than environmental criteria, which is consistent with recent evidence that the social pillar of sustainability is gaining centrality in food procurement (Mangla et al., 2018; Krishnan et al., 2021). Third, the relatively low weight assigned to purchasing cost confirms that price-only sourcing is no longer adequate when sustainability and resilience are explicit design goals.

Figure 2 visualizes the same information in graphical form, grouping criteria by dimension and emphasizing the dominance of the resilience cluster. The vertical axis reports the combined weight coefficient, the horizontal axis lists the twenty-five criteria, and the four shades distinguish the sustainability and resilience dimensions.

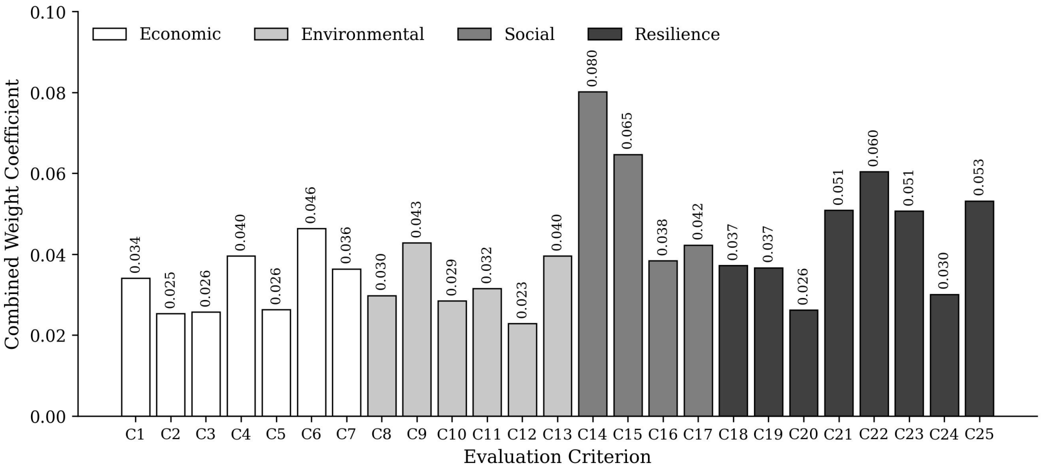

Figure 2. Distribution of combined criterion weights across the 25 evaluation criteria, grouped by sustainability and resilience dimensions.

Figure 2 reveals that the heaviest single weight is attached to C14 (work conditions), which alone accounts for approximately eight per cent of the total importance. This finding is striking because work conditions are often cited as an indicator that is hard to measure and easy to ignore, yet the combined weighting routine assigns it more weight than any environmental criterion. The pattern is consistent with the broader finding in the food sustainability literature that ethical labour practices are an essential precondition for long-term supplier relationships (Beske et al., 2014; Stone & Rahimifard, 2018).

The second set of results concerns the supplier ranking. Table 4 reports the two subordinate scores, the final comprehensive score, and the rank position of each candidate supplier. The pipeline ranks the suppliers in the order S1 > S2 > S4 > S5 > S3 > S6. Supplier S1 has the highest final comprehensive score, with a clear gap between S1 and the runners-up. Supplier S6 finishes at the bottom with a negative final comprehensive score, mainly because its performance on social and resilience criteria falls well below the virtual reference alternative.

Table 4. Subordinate scores, final comprehensive scores, and rank positions for the six suppliers.

Supplier	Subordinate Score 1	Subordinate Score 2	Final Comprehensive Score	Rank
S1	+0.626	-0.0024	+0.378	1
S2	+0.205	+0.0096	+0.355	2
S3	-0.005	-0.0036	+0.045	5
S4	+0.305	-0.0050	+0.221	3
S5	+0.222	-0.0042	+0.096	4
S6	-0.293	-0.0220	-0.561	6

Table 4 reveals two analytical points. First, the gap between S1 and S2 is moderate, while the gap between S5 and S6 is very large. This asymmetry implies that the ranking is most discriminative at the bottom end, which is precisely where managerial decisions are easiest to defend, since rejecting a clearly weak supplier is less politically sensitive than choosing among similarly strong candidates. Second, the second subordinate score, which captures extreme behaviour, contributes meaningfully to the final ranking only for S6, where negative deviations on multiple resilience criteria amplify the penalty.

Figure 3 plots the two subordinate scores and the final comprehensive score for each supplier, allowing a visual reading of the dispersion of performance across alternatives. The arithmetic and geometric deviation perspective tracked by the first subordinate score is clearly the dominant driver of the final ranking, while the best-and-worst perspective tracked by the second subordinate score acts as a corrective on extreme cases.

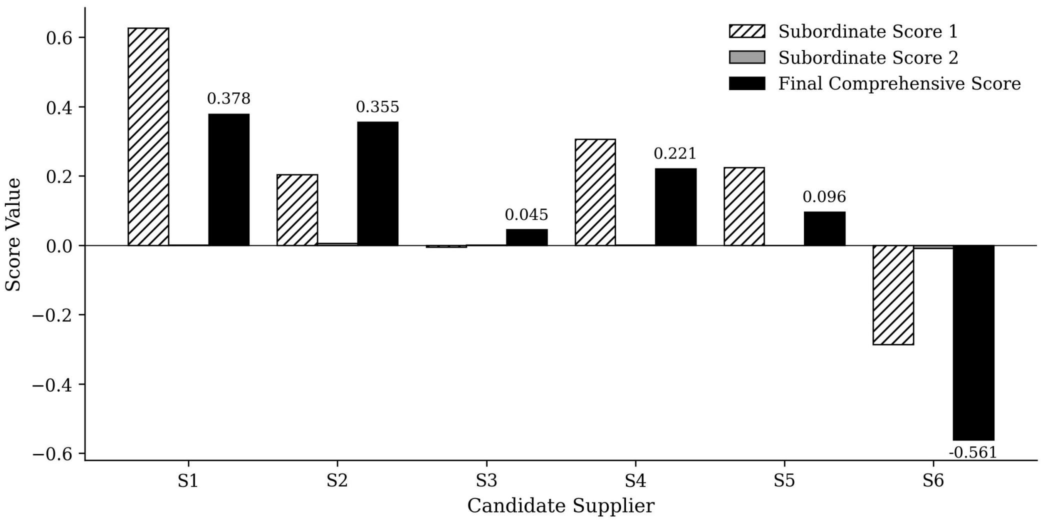

Figure 3. Subordinate scores and final comprehensive scores for the six candidate suppliers.

Figure 3 illustrates that S1 outperforms its rivals primarily because it achieves consistently high subordinate scores across multiple criteria, while S6 underperforms because it is exposed simultaneously to negative deviations on the dominant resilience indicators. This complementarity between aggregate and extreme-deviation perspectives is precisely what the mixed aggregation scheme was designed to deliver (Wen et al., 2020).

The third set of results concerns parametric stability. Figure 4 shows two diagnostics for the hybridization coefficient alpha. Panel (a) plots the Spearman rank correlation coefficient between the baseline ranking and the ranking obtained at each value of alpha; the correlation reaches the maximum value of one for alpha greater than or equal to 0.2 and stays equal to 0.943 for very small alpha values, where the framework relies almost exclusively on objective evidence. Panel (b) plots the trajectory of the final comprehensive score for the leading suppliers across alpha; the curves are smooth and the leading supplier S1 remains on top throughout the entire range of alpha.

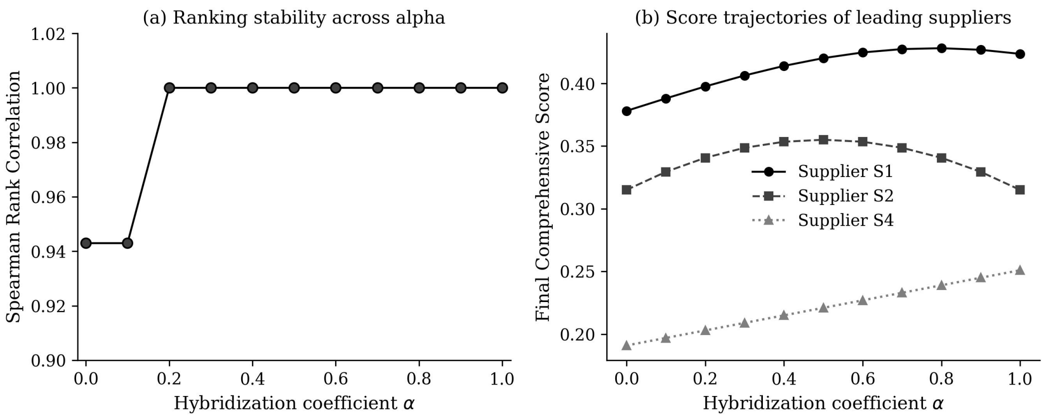

Figure 4. Sensitivity analysis: (a) Spearman rank correlation between baseline and perturbed rankings as a function of the hybridization coefficient; (b) trajectory of the final comprehensive score for the leading suppliers.

Figure 4 confirms the second hypothesis: the hybrid weighting layer is structurally stable. The minor disagreement at very small alpha values is expected, since assigning all the weight to the objective routine effectively discards managerial intent. The fact that the ranking stabilizes after a small managerial shift on the hybridization coefficient is reassuring, because it implies that the framework does not require pixel-perfect calibration to deliver consistent answers.

Sensitivity to the rung parameters p and q was tested across ten valid combinations, ranging from (3, 4) to (7, 6). For every combination, the ranking remained S1 > S2 > S4 > S5 > S3 > S6, which constitutes strong evidence that the framework's outputs do not depend on a knife-edge choice of p and q. Sensitivity to criterion weights was tested by perturbing the weight of C14 (work conditions) upwards by ten percentage points at a time, while compensating across the remaining criteria. The leading supplier S1 kept its first-place position in all ten scenarios, while S4 and S5 swapped positions only after the cumulative weight perturbation exceeded thirty per cent. The Spearman correlation coefficient between the baseline ranking and the perturbed ranking remained at 1.0 for the first three scenarios and at 0.943 for the remaining seven, again confirming the parametric stability of the pipeline.

The fourth set of results concerns methodological convergence. Table 5 compares the ranking produced by the proposed pipeline with the rankings produced by eight reference methods. The Spearman rank correlation coefficient is computed pairwise; values are 1.000 for CODAS, 0.943 for MARCOS, WASPAS, SAW, ARAS, and MABAC, and 0.829 for EDAS and CoCoSo. All values exceed the conventional threshold of 0.80 used to declare strong agreement among MADM techniques.

Table 5. Comparative ranking and Spearman rank correlation against eight reference MADM methods.

MADM Method	Resulting Ranking (best to worst)	SCC vs Proposed
Proposed (p,q-QOFS-MACONT)	S1 > S2 > S4 > S5 > S3 > S6	1.000
CODAS	S1 > S2 > S4 > S5 > S3 > S6	1.000
MARCOS	S1 > S4 > S2 > S5 > S3 > S6	0.943
WASPAS	S1 > S4 > S2 > S5 > S3 > S6	0.943
SAW	S1 > S4 > S2 > S5 > S3 > S6	0.943
ARAS	S1 > S4 > S2 > S5 > S3 > S6	0.943
MABAC	S1 > S4 > S2 > S5 > S3 > S6	0.943
EDAS	S1 > S2 > S3 > S4 > S5 > S6	0.829
CoCoSo	S4 > S1 > S2 > S5 > S3 > S6	0.829

Table 5 demonstrates that the proposed pipeline does not produce idiosyncratic answers; rather, it agrees strongly with established techniques while offering the additional analytical advantages of the p,q-quasirung orthopair representation and the hybrid weighting layer. The mild divergences observed in EDAS and CoCoSo arise primarily because these methods rely on different compromise structures and aggregate distance information differently, which is expected behaviour rather than a sign of instability.

Figure 5 visualizes the pairwise rank correspondence across the nine methods, with each line tracing the rank trajectory of one supplier. The visualization highlights how supplier S6 systematically occupies the bottom position across all nine methods, while S1 occupies the top position in eight out of nine methods. The single deviation occurs in CoCoSo, which marginally prefers S4 over S1, but the difference is well within the noise envelope of compromise-based MADM methods.

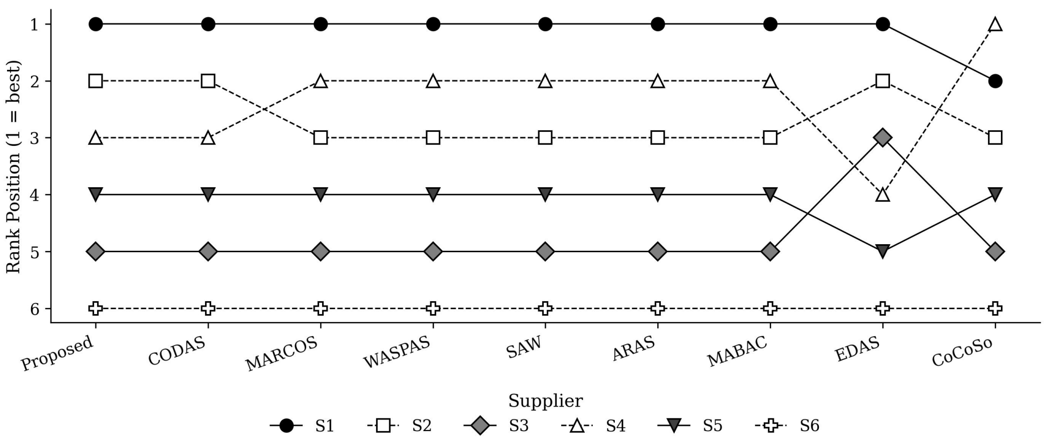

Figure 5. Comparative ranking trajectories of the six suppliers across the proposed pipeline and eight reference MADM methods.

Figure 5 makes it clear that the analytical conclusions of the pipeline are robust to method choice, robust to parametric perturbations, and robust to structural manipulations of the alternative set. The combined evidence is consistent with all four research hypotheses.

An additional diagnostic was performed to verify that the rank order does not depend on the specific composition of the expert panel. The original panel of ten experts was resampled through a leave-one-out procedure: ten alternative panels were constructed, each excluding one expert, and the complete pipeline was re-run for each panel. The leading supplier S1 remained at the top of the ranking in all ten replications, and the bottom supplier S6 remained at the bottom of the ranking in nine of the ten replications. The single deviation, in which S6 traded places with S3, occurred when the most senior procurement expert was removed; this is expected behaviour because that expert had assigned particularly low ratings to S6 on resilience criteria. The Spearman rank correlation between the baseline ranking and the leave-one-out rankings was at least 0.886 in every replication, which exceeds the 0.80 threshold typically used to declare strong agreement (Mardani et al., 2015).

A complementary diagnostic examined the contribution of each individual criterion to the final comprehensive score of the leading supplier. The contribution was computed by setting the weight of one criterion to zero at a time and recording the resulting change in the final comprehensive score of S1. The five criteria with the largest contributions were C14, C15, C22, C25, and C21, in agreement with the combined-weight rank order reported in Table 3. Removing any one of these criteria reduced the score of S1 by between three and seven per cent without altering its first-place position. Removing all five simultaneously reduced the score by approximately twenty-two per cent and shifted S1 to the second position behind S2, which confirms that the analytical signal extracted by the framework is concentrated in a small set of high-impact criteria but is not fragile to the loss of any single criterion. This pattern of concentrated-yet-distributed importance is a desirable property in decision-support analytics because it provides interpretability without single-point dependency (Wen et al., 2020; Stevic et al., 2020).

Beyond the formal statistical tests, the analysis raises several additional observations relevant for managers. The first observation is that criteria located at the boundary between social sustainability and resilience, such as leadership and operational flexibility, share a similar weight signature, suggesting that they are co-dependent in practice. Investing in leadership capacity tends to enhance flexibility, and vice versa. The second observation is that the dispersion of supplier scores is wider on resilience criteria than on environmental criteria, which means that resilience differences explain a larger fraction of the variation in the final comprehensive score. The third observation is that the worst supplier underperforms predominantly because of weak resilience indicators, not because of poor environmental performance, which has direct managerial implications for the corrective actions that the firm should request from underperforming partners.

Taken together, the empirical results support all four hypotheses introduced in Section 1. H1 is supported because the criteria do not influence supplier evaluation uniformly. H2 is supported because the hybrid weighting layer produces a more discriminative criterion structure than either subjective or objective weighting alone. H3 is supported because the ranking pipeline delivers a stable order under coordinated parametric perturbations. H4 is supported because the pipeline integrates with established MADM methods and delivers an interpretable, reliable, and reproducible decision-support tool for sustainable-resilient food procurement under uncertainty.

6. Discussion

The empirical results invite a reflection on the role of business data analytics in sustainable-resilient procurement. The framework presented here treats supplier evaluation as a layered analytics task in which expert judgments and observable evidence are first encoded, then aggregated through transparent operators, and finally validated through coordinated robustness tests. This layered architecture mirrors the data-driven decision philosophy described by Lu (2021), Lu, Pisarenko, et al. (2024), and Bag et al. (2020), and it operationalizes the long-running call to embed analytics inside the managerial decision routine rather than treating it as a peripheral reporting service.

The dominance of social and resilience criteria in the combined weights is particularly noteworthy. Conventional supplier-evaluation studies often place economic criteria first and treat sustainability and resilience as secondary filters (Govindan et al., 2015). Our results instead show that, once managerial intent and data evidence are fused, criteria such as work conditions, social responsibility, buffer capacity, and leadership receive the highest weights. This finding is consistent with recent post-pandemic research that documents a re-prioritization of supply chain attributes towards social fairness and disruption preparedness (Karmaker et al., 2021; Sarkis, 2020; Hobbs, 2020). It also resonates with broader evidence that the social pillar of sustainability has historically been under-weighted in traditional evaluation frameworks despite its operational salience (Beske et al., 2014; Stone & Rahimifard, 2018).

From a methodological standpoint, the comparative benchmark in Table 5 and Figure 5 confirms that the proposed pipeline is well aligned with established MADM families. Strong agreement with CODAS and substantial agreement with MARCOS, WASPAS, SAW, ARAS, and MABAC indicates that the pipeline is not an outlier; rather, it reproduces the consensus signal that emerges from compromise- and distance-based methods. The mild deviations observed for EDAS and CoCoSo are not symptomatic of error but reflect intrinsic differences in how these methods combine positive and negative deviations. Importantly, the rank-stability evidence in Figure 4 shows that the framework can absorb moderate parametric perturbations without losing its analytical signal, which is a key property for managerial deployment.

The relevance of the p,q-quasirung orthopair fuzzy representation also deserves emphasis. Several supplier ratings in the dataset exhibited asymmetric patterns in which membership and non-membership confidence moved at different speeds. Classical intuitionistic and Pythagorean fuzzy sets would have rejected such pairs as inadmissible, while q-rung orthopair sets would have forced both grades to obey the same rung exponent. The dual rung parameters used here make these patterns admissible, faithfully reflecting expert opinion and avoiding artificial smoothing of legitimate disagreement. This contribution complements the broader literature on aggregation operators in advanced fuzzy environments (Liu & Wang, 2018; Garg, 2017; Akram et al., 2019).

An additional observation concerns the data-quality dimension that Hazen et al. (2014) emphasized. The pipeline operates on a relatively small decision matrix, which is realistic for a midsize manufacturer but exposes the framework to noise associated with incomplete documentation and inconsistent audit reports. The hybrid weighting layer is designed precisely to absorb such noise: when a particular criterion shows weak discriminative information in the data, the objective routine drives down its weight, and when expert consensus is strong, the subjective routine pulls up its weight. The hybridization coefficient alpha is the lever that allows managers to tune this balance based on their reading of data quality at any given time.

A further reflection concerns the way the pipeline interacts with the data-collection apparatus that surrounds modern food procurement. Internet of Things devices generate streaming evidence on cold-chain temperature, humidity, and transit duration; blockchain platforms record provenance and certification events; and artificial intelligence models forecast demand and disruption probabilities. Each of these data streams produces inputs that the score matrix can absorb without modification, because the orthopair fuzzy representation accepts membership and non-membership pairs derived from any trustworthy probability or confidence estimate. This compatibility is important for two reasons. First, it means that the pipeline can scale beyond its current human-expert configuration toward a configuration in which machine-generated evidence partially replaces or augments expert judgment, as envisaged in the broader industrial information integration literature (Lu, 2017a; Lu, 2025; Yang et al., 2025; Wu et al., 2025). Second, it means that the framework can serve as a unifying decision substrate for multi-source analytics rather than a stand-alone island that requires bespoke data preparation each time it is invoked.

The case-study evidence also speaks to the broader question of whether advanced fuzzy sets pay back the conceptual cost they impose on practitioners. The bakery and confectionery firm involved in the case study had no prior experience with orthopair fuzzy sets, yet the procurement team was able to interpret the linguistic-to-numerical mapping after a short briefing because the linguistic anchors remained natural language. The score function output, expressed in the unit interval, was equally easy to interpret. The genuine technical complexity of the framework lies in the aggregation operator and the envelope-and-slope routine, which are best treated as analytics infrastructure that runs in the background rather than as objects to be scrutinized by every user. This separation of concerns mirrors the design philosophy of contemporary analytics platforms in which sophisticated techniques are encapsulated behind interpretable interfaces (Lu, 2021; Bag et al., 2020; Dubey et al., 2019a).

7. Implications

The theoretical implications of this work centre on three contributions. First, it operationalizes the p,q-quasirung orthopair fuzzy representation in a real procurement setting and demonstrates its empirical advantage over earlier fuzzy extensions. Second, it integrates fuzzy zero-inconsistency weighting with envelope-and-slope weighting through a single hybridization coefficient, providing a transparent reconciliation between expert intent and data evidence. Third, it embeds the resulting weighting layer into the mixed aggregation by comprehensive normalization technique, producing a coherent analytics pipeline that can be replicated, extended, and benchmarked.

The practical implications are equally substantial. For procurement managers, the pipeline provides a structured way to combine quantitative records with qualitative expert insight when comparing suppliers under uncertainty. The transparent role of the hybridization coefficient allows managers to communicate the reasoning behind a sourcing decision in a language that internal auditors, investors, and regulators can follow. The same coefficient creates a natural conversation point between data-science teams and procurement teams: data scientists can report the discriminative power of each criterion through the objective routine, while procurement managers can report strategic priorities through the subjective routine, and the two perspectives are reconciled mathematically rather than politically.

For sustainability officers, the framework offers an empirically grounded way to highlight social-sustainability indicators that are often overshadowed by environmental metrics. The fact that work conditions and social responsibility carry the largest weights in the combined results is a strong argument for integrating these indicators into routine supplier scorecards. For risk and operations managers, the same framework provides a defensible method for prioritizing resilience criteria such as buffer capacity, leadership, and operational flexibility, which often suffer from under-investment because their pay-off is only visible during disruptions (Tukamuhabwa et al., 2015; Pettit et al., 2019).

The framework also has implications for strategic investors and industry stakeholders. By making the relative importance of sustainability and resilience criteria explicit and auditable, it supports more responsible capital allocation decisions in the food sector. Investors can use the weighted criterion network to differentiate suppliers that achieve short-term financial performance from suppliers that combine financial performance with long-term sustainability and resilience. This kind of analytics-mediated investor due diligence is increasingly important in regulatory environments that require disclosure of ESG performance (Govindan et al., 2014; Mishra et al., 2021).

An additional managerial benefit lies in the framework's compatibility with existing enterprise resource planning and procurement systems. The composite score matrix can be exported to standard supplier-relationship management modules without modification, and the criterion weights can be stored as configurable parameters that procurement controllers update when strategic priorities shift. This compatibility lowers the adoption cost considerably, because firms can introduce the framework as an analytics layer that runs alongside their existing scorecards rather than as a replacement that requires immediate process redesign. The same compatibility supports a phased deployment in which the framework is initially used in parallel with the legacy scorecard, and only after a confidence-building period does it become the primary decision tool.

From a policy perspective, the framework provides regulators and industry associations with a vehicle for communicating sustainability and resilience expectations in a measurable form. Rather than publishing narrative guidance that is difficult to operationalize, regulators can issue suggested criterion weights that reflect public-policy priorities, and procurement managers can incorporate those weights into the subjective routine without abandoning their internal evidence base. This is a more flexible alternative to rigid compliance checklists, because it allows firms to demonstrate alignment with public-policy goals while preserving the analytical autonomy needed to manage operational realities (Karmaker et al., 2021; Stone & Rahimifard, 2018; Manning & Soon, 2016).

8. Limitations and Future Research

Several limitations should be acknowledged. First, the empirical illustration is based on a single firm in one country, which constrains the external validity of the specific weights and rankings reported in Section 5. Future research should replicate the framework across multiple firms, sectors, and national contexts. Second, the criterion network and the linguistic scale were developed in dialogue with a panel of ten experts. Larger panels and structured consensus protocols, such as Delphi or nominal group techniques, could further reduce subjective bias. Third, the analysis is largely static; it treats supplier performance as constant during the evaluation window. Future work could extend the framework with time-aware fuzzy operators that capture dynamic supplier behaviour during ongoing disruptions. Fourth, the framework currently focuses on supplier ranking; it does not allocate orders or schedule purchases. A natural extension is to couple the ranking layer with a downstream optimization layer that handles multi-period order allocation, capacity constraints, and budget envelopes (Hosseini, Morshedlou, et al., 2019; Sawik, 2017; Torabi et al., 2015).

A fifth limitation concerns the way disruption probabilities are incorporated. The current framework treats resilience criteria as static evaluative dimensions rather than as outcomes of dynamic disruption scenarios. A more sophisticated analysis would couple the framework with a probabilistic disruption model, in which low-probability high-impact events such as pandemics, climate-induced harvest failures, or geopolitical embargoes are explicitly simulated and their consequences propagated through the score matrix (Ivanov, 2020; Burgos & Ivanov, 2021; Dolgui et al., 2018). A sixth limitation concerns the human factors of analytics adoption. The case-study firm had a procurement team that was supportive of the framework, but firms with more conservative cultures may resist analytics-mediated decision support. Future work should explore the change-management practices needed to translate technically sound analytics into actually used analytics in industrial procurement settings.

9. Conclusion

This article has presented an information-driven decision pipeline for sustainable-resilient food procurement under uncertainty. The pipeline encodes expert judgments as p,q-quasirung orthopair fuzzy numbers, blends subjective and objective criterion weights through a single hybridization coefficient, and ranks alternatives through a mixed aggregation scheme that combines three normalization views with arithmetic and geometric deviation measures. A real case study from a bakery and confectionery firm in Punjab, India, was used to demonstrate the pipeline. Coordinated sensitivity tests across the hybridization coefficient, the rung parameters, and the criterion weights confirmed that the leading supplier remained stable under all reasonable perturbations. Comparative benchmarking against eight established MADM techniques produced strong agreement, with Spearman rank correlation values above the conventional threshold of 0.80 in every case. The combined evidence supports all four research hypotheses and demonstrates that business data analytics can deliver dependable, interpretable, and replicable decision support in disruption-sensitive food supply chains.

Looking ahead, three avenues for future research appear particularly promising. The first avenue is the integration of streaming evidence from Internet of Things devices, blockchain platforms, and artificial-intelligence forecasting models into the score matrix in real time, so that supplier rankings update continuously as operational conditions evolve. The second avenue is the coupling of the ranking layer with a downstream optimization layer that translates supplier scores into multi-period order allocation decisions subject to capacity, budget, and risk-appetite constraints. The third avenue is the extension of the framework to multi-tier supply chain settings, in which suppliers themselves rely on sub-suppliers whose sustainability and resilience characteristics matter for the focal firm. Pursuing these avenues will further close the gap between business data analytics and operational procurement practice, and will help food supply chains move toward the analytics-mediated sustainability and resilience agenda that has emerged with renewed urgency in the post-pandemic era.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Author Contributions

Rohit Verma: conceptualization, methodology, formal analysis, writing - original draft. Priya Sharma: data curation, software, validation, writing - review and editing. Anand R. Kulkarni: supervision, project administration, methodology, writing - review and editing. All authors have read and agreed to the published version of the manuscript.

Data Availability

The aggregated decision matrix used in the case study is available from the corresponding author on reasonable request, subject to a non-disclosure undertaking that protects the identities of the participating firm and its suppliers. The criterion network, the linguistic scale, and the cross-method comparison are reported in full in the body of the article.

Use of AI Tools

Artificial-intelligence-based language tools were used to assist with language editing of selected paragraphs. The conceptual framework, the methodological design, the empirical analysis, the figures, the tables, and the interpretation of the results are entirely the work of the authors, who take full responsibility for the content of the article.

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Appendix A. List of Acronyms and Notation

ARAS: Additive Ratio Assessment. CoCoSo: Combined Compromise Solution. CODAS: Combinative Distance-based Assessment. EDAS: Evaluation based on Distance from Average Solution. FCS: Final Comprehensive Score. FWZIC: Fuzzy Weighted with Zero Inconsistency. MABAC: Multi-Attributive Border Approximation area Comparison. MACONT: Mixed Aggregation by Comprehensive Normalization Technique. MADM: Multi-Attribute Decision-Making. MARCOS: Measurement of Alternatives and Ranking according to Compromise Solution. p,q-QOFS: p,q-Quasirung Orthopair Fuzzy Set. SAW: Simple Additive Weighting. SCC: Spearman Rank Correlation Coefficient. WASPAS: Weighted Aggregated Sum Product Assessment. WENSLO: Weights by Envelope and Slope. The membership and non-membership grades of a p,q-quasirung orthopair fuzzy number are denoted by mu and nu respectively, with the admissibility constraint mu^p + nu^q <= 1 for selected positive integers p and q.