Green Supplier Prioritization in Food Manufacturing: A Hybrid Fuzzy Decision Model for Sustainability and Resilience Performance

Minghao Chen[1], Yilin Zhao[2], Rui Wang[3], Lijun Tang[4,*]
[1] School of Management, Henan University of Technology, Zhengzhou, 450001, China
[2] College of Food Science and Engineering, Bohai University, Jinzhou, 121013, China
[3] School of Business Administration, Shandong Technology and Business University, Yantai, 264005, China
[4] School of Economics and Management, Hubei University of Technology, Wuhan, 430068, China
* Corresponding Author. Email: tanglijun@hbut.edu.cn

Abstract

This study develops a hybrid fuzzy decision model for prioritizing green suppliers in food manufacturing where procurement teams must balance price, product safety, carbon performance, social responsibility, and disruption recovery. Unlike conventional supplier selection models that focus mainly on cost or quality, the proposed model integrates sustainability and resilience performance into one auditable prioritization process. The model combines a fuzzy linguistic evaluation scale, subjective expert weighting, objective CRITIC-based contrast weighting, and a fuzzy TOPSIS ranking procedure. A case study of six candidate suppliers for a mid-sized Chinese food manufacturer is used to demonstrate the model. Sixteen criteria are organized into four dimensions: economic reliability, environmental performance, social and food-safety responsibility, and operational resilience. The results show that recovery speed, food safety governance, buffer capacity, multi-source adaptability, and labor and welfare compliance receive the highest hybrid weights. Supplier A1 obtains the highest final fuzzy closeness score, followed by A5 and A3. Sensitivity tests indicate that the top two suppliers remain stable when the balance between subjective and objective weights changes, while the middle-ranked suppliers are more sensitive to the decision maker's strategic emphasis. The findings suggest that food manufacturers should not treat green supplier selection as a single environmental screening problem. Instead, it should be designed as a portfolio decision that links green capability, product safety, traceability, and resilience. The study contributes a practical fuzzy decision-support framework for procurement managers and extends green supply chain research by demonstrating how sustainability and resilience can be jointly operationalized in supplier prioritization.

Keywords: *green supplier prioritization; food manufacturing; fuzzy decision model; sustainability performance; supply chain resilience; CRITIC; fuzzy TOPSIS*

Article History:

Received: July 11, 2024

Revised: September 21, 2024

Accepted: November 12, 2024

Available Online: December 30, 2024

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2025.020401

Green Supplier Prioritization in Food Manufacturing: A Hybrid Fuzzy Decision Model for Sustainability and Resilience Performance

1. Introduction

Food manufacturers face a procurement environment in which the supplier decision no longer rests on lowest price, acceptable quality, and delivery punctuality alone. Raw material suppliers, packaging vendors, cold-chain logistics providers, and ingredient processors now influence the carbon profile, food safety exposure, social reputation, and recovery capacity of the focal manufacturer. Green supplier prioritization is therefore not a peripheral purchasing activity but a strategic decision that determines whether food manufacturing can meet cost expectations while also responding to climate pressure, consumer scrutiny, and uncertain disruptions. The sustainable supply chain literature has long argued that environmental and social criteria must be embedded in operational choices rather than added after the sourcing decision has been completed (Seuring & Müller, 2008).

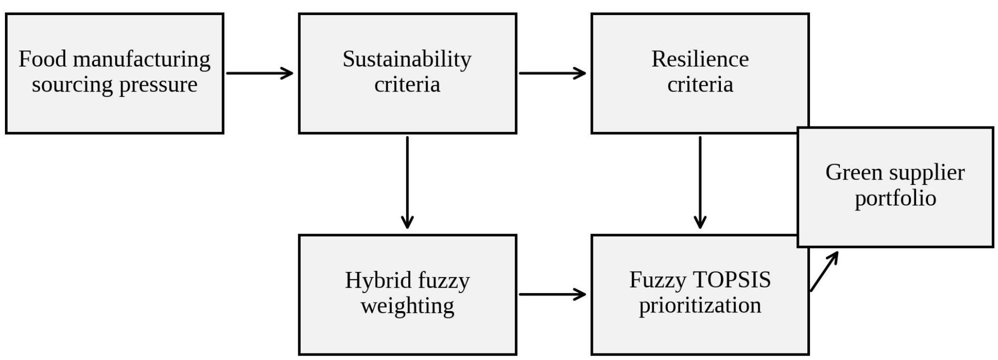
This need is particularly visible in food manufacturing. Food products are perishable, safety-sensitive, and often dependent on agricultural inputs that are exposed to weather shocks, disease risk, seasonal variability, and logistics congestion. A supplier that appears attractive through a narrow cost lens may create hidden exposure through weak traceability, unstable cold storage, limited recovery capacity, or poor environmental documentation. Earlier work on the food industry emphasizes that sustainable supply chain management requires dynamic capabilities because food firms must repeatedly reconfigure sourcing practices when ecological, regulatory, and demand conditions change (Beske et al., 2014).

Green supplier prioritization also differs from general supplier selection because several evaluation dimensions are qualitative and ambiguous. Procurement specialists may describe a supplier's traceability as strong, moderate, or weak rather than calculate a precise traceability score. Environmental managers may know that a packaging vendor has a better carbon profile than another vendor but lack exact life-cycle data. Food safety officers may trust one supplier's hazard analysis routines more than another's but express that trust linguistically. Fuzzy set theory provides a natural basis for representing such ambiguous evaluations because it converts imprecise linguistic statements into analyzable values without forcing false precision (Zadeh, 1965).

A second challenge is that food manufacturers must balance sustainability with resilience. A supplier with a strong green certification portfolio is not necessarily resilient if it relies on one production site, one logistics route, or a fragile inventory policy. Conversely, a supplier with high buffer capacity and quick recovery may perform poorly on water management or recyclable packaging. Supply chain resilience research suggests that firms should evaluate the ability to absorb disturbance, recover quickly, and maintain continuity when unexpected events occur (Ponomarov & Holcomb, 2009). In food manufacturing, those resilience capabilities interact directly with sustainability because shortages and disruptions can increase waste, emergency transport, and safety risk.

The growing importance of digitalization further complicates the prioritization problem. Sensors, enterprise resource planning systems, blockchain records, and supplier portals increase visibility, but they also produce new forms of data dependency and cyber exposure. Industry 4.0 research shows that digital technologies reshape industrial information integration, process coordination, and supply chain decision-making (Lu, 2017). For a food manufacturer, the relevant question is not simply whether a supplier uses digital tools, but whether those tools support reliable traceability, timely warning, and responsible governance. Green supplier prioritization must therefore connect digital monitoring with sustainability and resilience outcomes.

The present study responds to these challenges by proposing a hybrid fuzzy decision model for food manufacturing. The model combines expert judgments, fuzzy linguistic conversion, subjective weighting, objective contrast weighting, and fuzzy TOPSIS ranking. This structure is designed for procurement settings where decision makers have both managerial priorities and partially observable supplier performance information. The subjective component captures what managers consider strategically important, while the objective component captures the dispersion and contrast in supplier data. The final ranking is therefore not determined by one decision perspective only, but by a combined structure that can be reviewed and adjusted.



Integrated sustainability-resilience logic converts ambiguous expert judgments into auditable supplier priorities.

Figure 1. Conceptual framework for green supplier prioritization in food manufacturing

As shown in Figure 1, the framework begins with the sourcing pressure of food manufacturing and then translates the pressure into sustainability and resilience criteria. These criteria are evaluated through a hybrid fuzzy weighting process and a fuzzy prioritization process. The output is not merely a single winning supplier; it is a supplier portfolio logic that shows which suppliers are dominant, which are acceptable for backup sourcing, and which require improvement before strategic use. This logic follows the view that sustainable supply chain management should combine environmental, social, and economic goals rather than optimize one isolated indicator (Carter & Rogers, 2008).

The article makes three contributions. First, it develops a food-manufacturing-specific criteria system that integrates economic reliability, environmental performance, social and food safety responsibility, and operational resilience. Second, it builds a hybrid fuzzy decision model that combines subjective managerial knowledge with objective information contained in the supplier evaluation matrix. Third, it demonstrates how the model can produce a stable ranking and a set of managerial interpretations, rather than treating the mathematical ranking as a black box. This emphasis on interpretable analytics is consistent with management analytics research that highlights the role of structured data-driven reasoning in modern business decision-making (Lu et al., 2024).

The remainder of the paper is organized as follows. Section 2 reviews the literature on green supplier selection, food supply chain sustainability, resilience, fuzzy decision modeling, and digital supplier governance. Section 3 presents the criteria system and the hybrid fuzzy methodology. Section 4 describes the case setting, supplier profiles, expert evaluation procedure, and data construction. Section 5 reports criteria weights, supplier rankings, and sensitivity analysis. Section 6 discusses theoretical and managerial implications. Section 7 concludes the study and identifies limitations and future research directions.

2. Literature Review and Research Gap

2.1 Green and sustainable supplier selection

Supplier selection has been one of the most researched decision problems in operations and supply chain management because supplier performance influences cost, quality, flexibility, and customer service. Traditional models often emphasized economic indicators, but green supply chain management extended the supplier decision by requiring environmental criteria such as pollution prevention, resource conservation, eco-design, green packaging, and compliance with environmental regulations. Early studies on green supply chain management show that environmental practices are shaped by both operational capability and organizational pressure (Zhu et al., 2008).

Green supplier selection became more systematic when researchers began to connect supplier assessment with multi-criteria decision-making. Environmental supplier assessment requires trade-offs because a supplier can be strong in documentation but weak in energy efficiency, or strong in recycling but weak in delivery stability. The use of environmental criteria in supplier assessment was first developed as a practical procurement response to broader sustainability pressures (Handfield et al., 2002). In later work, green supplier selection models became more formal by combining criteria structures, expert judgments, and ranking methods.

Sustainable supplier selection further broadens the decision by incorporating the triple bottom line. Economic criteria remain necessary because food manufacturers cannot ignore total cost, quality stability, and delivery reliability. Environmental criteria are necessary because sourcing decisions influence carbon emissions, water use, waste generation, and packaging impacts. Social criteria are also necessary because labor standards, food safety governance, community responsibility, and transparency influence legitimacy. A comprehensive sustainable supply management perspective requires firms to consider these criteria as interdependent rather than independent boxes (Ageron et al., 2012).

Several studies demonstrate that sustainable supplier evaluation benefits from fuzzy methods because linguistic judgments appear frequently in practice. For instance, green certifications, collaboration quality, and social compliance are difficult to measure with the same precision as cost or defect rate. A fuzzy supplier evaluation approach captures this imprecision and reduces the risk that qualitative criteria are excluded merely because they are less measurable (Chen et al., 2006). This insight is important for food manufacturers because traceability, hygiene culture, and supplier learning ability are often evaluated through audits and expert interpretation.

A related stream of research examines sustainable supplier selection under incomplete information. Incomplete information is common in procurement because suppliers may provide partial carbon data, limited water-use evidence, or different forms of audit documentation. Fuzzy multi-criteria frameworks are useful in such settings because they preserve the direction and intensity of expert opinion even when numerical data are not fully available (Büyüközkan & Çifçi, 2011). The present study follows this logic but adapts it to food manufacturing by adding resilience as a fourth decision dimension.

The literature also shows that sustainable supplier selection should not be treated as a one-time compliance checklist. Suppliers must be monitored, developed, and sometimes re-ranked when the buyer's strategy changes. Reviews of sustainable supplier management emphasize that selection, monitoring, and development models should be linked if firms want procurement decisions to support long-term sustainability outcomes (Zimmer et al., 2016). This study therefore interprets prioritization results as a starting point for supplier development and portfolio design, not simply as a replacement rule.

2.2 Food manufacturing and sustainability-resilience trade-offs

Food manufacturing presents a distinctive context for green supplier prioritization because raw materials are perishable and because product safety cannot be separated from supplier capability. A supplier that is environmentally strong but weak in safety governance can damage the buyer's reputation and create regulatory risk. A supplier that is operationally reliable but environmentally weak can prevent the buyer from meeting carbon, packaging, or resource efficiency commitments. The agri-food supply chain literature highlights the need for hierarchical decision structures because food supply chains involve multiple interacting performance layers (Tsolakis et al., 2014).

Food supply chains also contain strong collaboration requirements. Sustainability outcomes depend on the behavior of farmers, processors, packaging providers, logistics firms, retailers, and regulators.

Collaboration affects information sharing, joint problem solving, and improvement speed, especially when sustainability goals require changes in production routines. A systematic review of agri-food collaboration emphasizes that behavioral factors, trust, and coordination mechanisms shape the success of sustainability implementation (Dania et al., 2018). Supplier prioritization should therefore include transparency and relationship capability rather than focus only on audit scores.

Food manufacturing firms increasingly operate in supply networks rather than simple supply chains. A first-tier supplier may rely on sub-suppliers for additives, packaging materials, agricultural inputs, or logistics services. This multi-tier structure means that sustainability failures can be hidden below the first-tier supplier and may become visible only after a safety incident, labor controversy, or disruption. Research on sub-supplier management from a sustainable food supply chain perspective shows that focal firms need criteria that encourage visibility beyond direct transactional performance (Grimm et al., 2014).

Resilience is the second essential requirement. Food manufacturers must respond to harvest volatility, contamination events, transportation delays, temperature-control failures, and sudden demand shocks. The resilience literature distinguishes between vulnerability, capability, disruption absorption, recovery, and adaptation. A resilient supplier is not simply one that has never failed; it is one that has enough capacity, redundancy, knowledge, and responsiveness to continue supplying under stress. Conceptual resilience frameworks stress the need to evaluate both vulnerabilities and capabilities in order to understand true continuity potential (Pettit et al., 2010).

Resilience also has a strategic dimension. A supplier may be reliable under ordinary conditions but vulnerable to extreme events because it lacks alternative transport routes, emergency inventory, or cross-trained staff. Reviews of enterprise and supply chain resilience describe redundancy, flexibility, visibility, collaboration, and risk culture as recurring resilience principles (Kamalahmadi & Parast, 2016). For food manufacturing, these principles translate into buffer capacity, recovery speed, alternative sourcing arrangements, and digital monitoring capability, all of which are included in the criteria system of this study.

Sustainability and resilience are sometimes aligned but sometimes in tension. Local sourcing can reduce transport emissions and improve relationship control, but it may also increase geographic concentration risk. Lean inventory can reduce waste, but excessive leanness can reduce disruption absorption capacity. Reusable packaging can improve circularity, but it may require cleaning routines and reverse logistics capacity. Modern supply chain resilience research suggests that firms should avoid interpreting resilience as a narrow emergency response and instead connect it with long-term viability (Ivanov, 2020).

2.3 Fuzzy decision modeling for supplier prioritization

Multi-criteria decision-making is appropriate for supplier prioritization because decision makers must compare a finite set of suppliers against multiple conflicting criteria. Supplier selection reviews show that methods such as TOPSIS, VIKOR, AHP, fuzzy extensions, mathematical programming, and hybrid models have been widely applied to this problem (Ho et al., 2010). However, the practical value of any method depends on whether its assumptions match the procurement context. Food manufacturing requires a model that is understandable, auditable, and flexible enough to incorporate both expert judgment and measurable supplier information.

Fuzzy decision modeling begins from the idea that human judgments do not always have crisp boundaries. The difference between high and very high food safety governance, for example, is often gradual. Fuzzy set theory provides a mathematical language for such gradual membership (Bellman & Zadeh, 1970). Later extensions introduced richer ways to represent uncertainty, including membership and non-membership values, which are useful when decision makers simultaneously express support and hesitation (Atanassov, 1986). In this paper, triangular fuzzy numbers are used because they are transparent and familiar to managers.

Fuzzy TOPSIS is selected as the ranking mechanism because it is intuitive: a strong supplier should be close to the positive ideal solution and far from the negative ideal solution. The method is especially useful when the goal is to produce a relative priority order rather than an absolute performance certificate. The extension of TOPSIS to fuzzy group decision-making provides the methodological foundation for transforming linguistic evaluations into closeness coefficients (Chen, 2000). This study adapts that logic to the four-dimensional sustainability-resilience criteria structure.

The weighting process is equally important. If weights are derived only from expert opinion, the result can reflect managerial preference but may ignore the discriminatory power of observed supplier performance. If weights are derived only from data dispersion, the result can be objective but strategically thin. The CRITIC method addresses the objective side by considering contrast intensity and inter-criteria conflict, meaning that a criterion receives more weight when it varies across alternatives and carries information not duplicated by other criteria (Diakoulaki et al., 1995).

For the subjective side, step-wise comparative weighting is useful because experts often find it easier to judge the relative importance of adjacent criteria than to provide a complete pairwise matrix. Step-wise weight assessment reduces cognitive burden while still producing a structured priority vector (Kersuliene et al., 2010). In the proposed model, the subjective weights are obtained from expert ordering and relative importance ratios, while the objective weights are calculated from the supplier evaluation matrix. The final hybrid weight combines these two sources.

The broader MCDM literature confirms that no single method is universally best. Each method imposes a particular view of distance, compromise, dominance, or utility. Reviews of MCDM applications emphasize the value of method selection based on decision context and data characteristics rather than methodological fashion (Mardani et al., 2015). The model in this study is therefore designed to be simple enough for procurement use while still rigorous enough to support sustainability and resilience evaluation.

Fuzzy supplier-selection reviews further show that supplier evaluation often suffers from inconsistent criteria definitions and excessive technical complexity. When decision makers cannot explain the meaning of a criterion or how it affects the final ranking, the model may be mathematically elegant but managerially weak. A review of fuzzy MADM approaches argues that supplier selection models should be interpretable and should match the informational reality of the organization (Keshavarz Ghorabaee et al., 2017). This study addresses that concern by using a concise criteria system and reporting the managerial meaning of weights and rankings.

2.4 Digital traceability and green supplier governance

Digital technologies are increasingly relevant to green supplier prioritization because sustainability and resilience depend on information quality. Real-time monitoring, blockchain-enabled traceability, supplier portals, and analytics dashboards allow food manufacturers to observe temperature, inventory, delivery status, certification validity, and incident history. Research on blockchain in supply chain management highlights the potential of distributed records to improve trust and visibility, especially when multiple actors need to verify shared information (Saberi et al., 2019).

In food supply chains, digital traceability can support rapid recall, origin verification, and compliance documentation. Blockchain-enabled traceability models in agriculture show how digital records can connect production, processing, logistics, and retail information into an auditable chain of custody (Kamble et al., 2020). However, digital traceability is not an automatic solution. It must be combined with data governance, cyber security, supplier training, and clear responsibility allocation. Thus, the present criteria include digital monitoring capability but do not allow it to dominate the whole model.

The Internet of Things also matters because sensors can capture temperature, humidity, location, and equipment status in near real time. Food supply chain virtualization research shows that IoT technologies can create digital representations of physical flows and thereby improve coordination (Verdouw et al., 2016). For a manufacturer evaluating suppliers, IoT capability is relevant only when it leads to practical monitoring, warning, and corrective action. The model therefore treats digital monitoring as part of resilience performance rather than a separate technology prestige score.

Cybersecurity cannot be ignored when supplier information flows become digital. IoT and blockchain integration increases visibility but also expands the digital attack surface. Research on IoT cybersecurity highlights the need to protect connected devices, data transmission, and system integrity (Lu & Xu, 2019). In a food manufacturing context, a supplier with digital monitoring but weak data protection may introduce operational risk. The proposed model captures this issue through the information transparency and digital monitoring criteria, which are interpreted together during supplier review.

Artificial intelligence and analytics can further support supplier prioritization by detecting anomalies, forecasting disruptions, and learning from supplier performance histories. The evolution of AI research demonstrates that intelligent models have moved from narrow classification tasks toward broader decision support applications (Lu, 2019a). At the same time, procurement teams need transparent analytics. A score that cannot be explained will not easily be accepted by purchasing managers, food safety officers, or sustainability auditors. The fuzzy model proposed here provides a transparent intermediate approach between manual scoring and black-box prediction.

Blockchain and information systems research also suggests that technological adoption should be evaluated in relation to organizational processes. Implementing blockchain in information systems involves data standards, governance rules, integration costs, and user responsibilities (Lu, 2022). For supplier prioritization, this means that a supplier's digital maturity should not be assessed by the presence of a platform alone. The relevant question is whether digital records improve traceability, accountability, and disruption response in the buyer's sourcing system.

Recent reviews of Industry 4.0 applications emphasize that digital technologies can support industrial transformation, but adoption produces value only when it is aligned with operational needs and managerial capabilities (Lu, 2025). This study therefore incorporates digital monitoring as one resilience criterion among several. A supplier may achieve a high ranking by combining good digital capability with strong safety governance, buffer capacity, and environmental performance; it cannot compensate for poor sustainability simply by claiming advanced technology.

The research gap can now be summarized. Existing studies have developed many green or sustainable supplier selection models, but food manufacturing requires a framework that jointly handles sustainability, resilience, and fuzzy information. Models that focus on sustainability may miss disruption exposure. Models that focus on resilience may neglect carbon, packaging, labor, and food safety governance. Models that use only subjective weights may overfit managerial intuition, while models that use only objective weights may miss strategic priorities. The proposed hybrid fuzzy decision model addresses this gap through a transparent combined weighting and ranking procedure.

Supplier evaluation models have also evolved from narrow green screening toward more integrated sustainability logic. Grey and rough-set approaches show that sustainability can be embedded in supplier selection even when data are incomplete or partially qualitative (Bai & Sarkis, 2010). Quantitative reviews further indicate that sustainable supply chain models increasingly combine optimization, decision analysis, and performance measurement to support operational decisions (Brandenburg et al., 2014).

Resilience research provides a complementary foundation. The idea of building the resilient supply chain highlights visibility, collaboration, and flexible response as managerial capabilities rather than emergency slogans (Christopher & Peck, 2004). A systematic review of supply chain resilience research also shows that future studies should connect resilience capabilities with measurable decision processes (Hohenstein et al., 2015).

Digital transformation adds another layer to this challenge. Research on the ripple effect and supply chain risk analytics suggests that Industry 4.0 technologies can change how disruptions propagate and how firms detect them (Ivanov et al., 2019). Sustainable Industry 4.0 studies similarly argue that digitalization should support environmental and operational objectives together rather than operate as a separate technology agenda (Kamble et al., 2018).

Blockchain-based supplier governance is promising but difficult to implement. Adoption barriers include cost, governance uncertainty, technical integration, and partner readiness (Kouhizadeh et al., 2021). Reviews of blockchain and supply chain management integration also emphasize that traceability benefits depend on network participation and process redesign (Queiroz et al., 2019).

Earlier hybrid green supplier models demonstrate the usefulness of combining intelligent methods with multi-attribute decision analysis. Integrating artificial neural networks with MADA methods, for example, shows that supplier performance patterns can be learned while still supporting multi-criteria evaluation (Kuo et al., 2010). More recent big-data-oriented fuzzy models similarly point toward data-rich green supplier selection, although many firms still require simpler decision tools (Yildizbasi & Arioz, 2022).

The intuitionistic fuzzy sustainable supplier literature also reinforces the need to represent hesitation and incomplete preference information (Phochanikorn & Tan, 2019). Best-worst method research shows another route for deriving criteria weights from limited comparisons (Rezaei, 2015), and its later linear formulation improves consistency and computational convenience (Rezaei, 2016). The present study uses a simpler step-wise and CRITIC combination because the target setting is a procurement workshop with multiple criteria.

Green supply chain theory adds a governance perspective. Organizational reviews of green supply chain management show that environmental practices are influenced by institutions, resources, stakeholder pressure, and inter-organizational relationships (Sarkis et al., 2011). Collaboration research further indicates that resilience improves when partners share information and coordinate responses rather than protect isolated interests (Scholten & Schilder, 2015).

A further reason to combine sustainability and resilience is that resilience has multiple theoretical foundations, including complex adaptive systems, resource dependence, and risk management (Tukamuhabwa et al., 2015). Recent food supplier selection research using Pythagorean fuzzy decision methods confirms that sustainable food supplier selection is a highly uncertain decision problem and benefits from robust sensitivity testing (Wang et al., 2024).

Table 1. Literature positioning of the present study

Stream	Main contribution	Remaining gap addressed here
Green supplier selection	Environmental screening, compliance, eco-design	May underplay food safety and disruption recovery
Sustainable supplier selection	Economic, environmental, and social criteria	Often treats resilience as secondary
Food supply chain sustainability	Traceability, safety, collaboration, waste reduction	Needs stronger multi-criteria supplier prioritization tools
Supply chain resilience	Absorption, recovery, redundancy, adaptability	Often detached from green procurement criteria
Fuzzy MCDM	Linguistic judgment, uncertainty handling, ranking	Needs simple interpretation for procurement teams

3. Methodology

3.1 Decision problem and modeling assumptions

The decision problem is to prioritize candidate suppliers for a food manufacturer that wants to improve both green performance and resilience. The manufacturer has a finite set of candidate suppliers A = {A1, A2, ..., Am} and a set of evaluation criteria C = {C1, C2, ..., Cn}. Each supplier is evaluated by a panel that includes procurement, quality, production planning, logistics, food safety, and sustainability experts. Because experts do not always provide exact numerical values, the model allows linguistic assessments and converts them into triangular fuzzy numbers. This approach follows the general logic of supplier selection techniques that combine expert judgment with structured decision rules (Chai et al., 2013).

The model uses four assumptions. First, the criteria are assumed to be sufficiently independent for weighted aggregation, although some correlation is captured by the CRITIC objective weighting procedure. Second, expert judgments are assumed to reflect the company's procurement priorities, not universal weights for all food manufacturers. Third, each supplier can be evaluated against all criteria using available audit data, operational records, and expert interpretation. Fourth, fuzzy scores are used to represent ambiguity but are eventually defuzzified for ranking. These assumptions make the model practical for managers who need a repeatable decision process rather than a purely theoretical optimization model.

The use of a hybrid weighting procedure is motivated by the need to combine strategic intent and empirical contrast. A criterion such as recovery speed may be strategically important even if current suppliers have similar recovery scores. Conversely, a criterion such as carbon intensity may show strong variation across suppliers and thus contain important discriminatory information. Hybrid weighting reduces the risk of over-relying on either managerial preference or data dispersion. This idea is consistent with green supplier research that argues for balancing environmental priorities with operational performance evidence (Sarkis, 2003).

3.2 Criteria architecture

The criteria system contains 16 criteria organized into four dimensions. Economic reliability includes cost stability, quality consistency, delivery reliability, and process flexibility. Environmental performance includes carbon intensity, energy and water efficiency, green packaging readiness, and environmental certification. Social and food-safety responsibility includes food safety governance, labor and welfare compliance, information transparency, and local responsibility. Resilience includes recovery speed, buffer capacity, multi-source adaptability, and digital monitoring capability. This design reflects the view that sustainable supplier performance should integrate operational, environmental, and social considerations (Govindan et al., 2013).

Table 2. Evaluation criteria for green supplier prioritization

Code	Criterion	Dimension	Type
EC1	Total cost stability	Economic	Cost
EC2	Quality consistency	Economic	Benefit
EC3	Delivery reliability	Economic	Benefit
EC4	Process flexibility	Economic	Benefit
EN1	Carbon intensity	Environmental	Cost

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2025.020401

EN2	Energy and water efficiency	Environmental	Benefit
EN3	Green packaging readiness	Environmental	Benefit
EN4	Environmental certification	Environmental	Benefit
SO1	Food safety governance	Social	Benefit
SO2	Labor and welfare compliance	Social	Benefit
SO3	Information transparency	Social	Benefit
SO4	Local responsibility	Social	Benefit
RE1	Recovery speed	Resilience	Benefit
RE2	Buffer capacity	Resilience	Benefit
RE3	Multi-source adaptability	Resilience	Benefit
RE4	Digital monitoring capability	Resilience	Benefit

The criteria are selected to fit food manufacturing rather than general manufacturing. For example, food safety governance is placed within the social dimension because it concerns consumer protection, regulatory responsibility, and ethical production. Information transparency is also social because it allows the buyer and downstream customers to understand sourcing origin, certification status, and incident response. Recovery speed and buffer capacity are resilience criteria because they describe continuity under disturbance. Environmental certification is included, but it is not allowed to replace actual environmental performance such as carbon intensity and resource efficiency.

The criteria also reflect the distinction between green capability and green evidence. A supplier may claim to be green, but certification, packaging readiness, carbon profile, and water management provide different forms of evidence. Research on green supplier performance emphasizes that linguistic preferences are useful when exact data are incomplete but expert comparison remains possible (Shen et al., 2013). In the present model, the criteria are designed to capture both documented performance and managerial assessment.

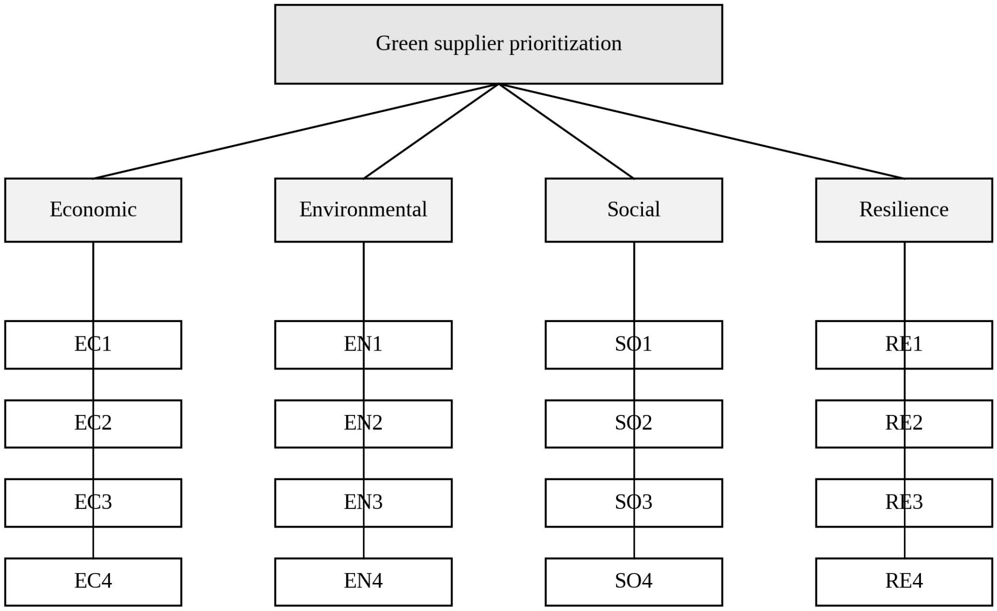


Figure 2. Criteria hierarchy of the proposed hybrid fuzzy model

Figure 2 illustrates the hierarchical criteria structure. The first level is the overall goal: green supplier prioritization. The second level contains four dimensions. The third level contains the 16 operational criteria. This hierarchy is intentionally compact. A larger set of criteria may appear more comprehensive, but it increases expert fatigue and can reduce reliability. A concise criteria system supports consistent evaluation across candidate suppliers while preserving the main sustainability-resilience trade-offs that food manufacturers face.

3.3 Linguistic scale and fuzzy evaluation

Experts evaluate suppliers using a seven-level linguistic scale ranging from very poor to excellent. Each linguistic term is represented by a triangular fuzzy number (l, m, u), where l is the lower bound, m is the most plausible value, and u is the upper bound. Triangular fuzzy numbers are selected because they are easy to explain and calculate. They also fit procurement workshops, where experts can agree that a supplier is between good and very good without forcing a precise value. The use of fuzzy linguistic evaluation follows the supplier selection tradition in which vague human judgments are formalized for group decision-making (Kannan et al., 2014).

Table 3. Linguistic scale and triangular fuzzy numbers

Linguistic term	Triangular fuzzy number	Interpretation
Very poor	(0.00, 0.00, 0.20)	Serious weakness; supplier is not suitable without major correction
Poor	(0.10, 0.25, 0.40)	Weak performance with substantial risk
Fair	(0.30, 0.45, 0.60)	Acceptable minimum with visible limitations

Moderate	(0.45, 0.60, 0.75)	Operationally acceptable but not strategically strong
Good	(0.60, 0.75, 0.90)	Strong performance with manageable weaknesses
Very good	(0.75, 0.88, 0.98)	Highly reliable performance
Excellent	(0.88, 1.00, 1.00)	Benchmark-level performance

For benefit criteria, a higher fuzzy score indicates better performance. For cost criteria, the value is transformed so that a higher score also indicates better performance. In this study, total cost stability and carbon intensity are treated as cost-related criteria, but they are converted into benefit-type evaluation scores during normalization. This convention simplifies interpretation because all final scores move in the same direction: higher means better. The approach is compatible with the TOPSIS logic of positive and negative ideal solutions (Opricovic & Tzeng, 2004).

If multiple experts evaluate the same supplier and criterion, their fuzzy numbers are aggregated by arithmetic averaging. The aggregated triangular fuzzy value is then defuzzified using the centroid formula $D = (l + m + u) / 3$ for the objective weighting and ranking procedures. This step reduces computational burden and supports managerial explanation. Although more complex fuzzy representations exist, a simple triangular fuzzy scale is often more suitable for organizational adoption because decision makers can understand how judgments become scores.

3.4 Subjective, objective, and hybrid weights

The subjective weighting procedure begins with expert ordering of the criteria within and across dimensions. Experts first identify the most influential criteria for green supplier prioritization in the food manufacturing context. They then provide comparative importance ratios between adjacent criteria. The ratios are converted into a normalized subjective weight vector. This procedure is less demanding than a full pairwise comparison matrix and is appropriate when a panel must evaluate many criteria in a limited workshop time. The structure also respects the insight that sustainable supplier selection must reflect managerial priorities, not only data-driven variation (Pagell & Wu, 2009).

Objective weights are calculated using the CRITIC logic. After defuzzified supplier scores are normalized, the standard deviation of each criterion is calculated to measure contrast intensity. A criterion with greater variation across suppliers can better discriminate among alternatives. The correlation between criteria is also calculated to identify redundancy. A criterion receives higher objective importance when it has high contrast and low redundancy with other criteria. This means that objective weighting rewards criteria that add new information to the decision matrix rather than merely repeating existing signals.

The hybrid weight of criterion j is calculated as wj = alpha wsj + (1 - alpha) woj, where wsj is the subjective weight, woj is the objective weight, and alpha is the decision maker's preference for subjective strategic judgment. In the base case, alpha = 0.55 because the company wants managerial priorities to have a slightly higher role than statistical contrast, while still preserving objective information. Sensitivity analysis varies alpha from 0 to 1 to test whether the ranking depends on this assumption.

The hybrid weighting procedure is valuable because food manufacturing involves both hard data and judgment. For example, delivery reliability may be measured through on-time delivery records, but the seriousness of a quality deviation depends on product category and regulatory context. Labor compliance may be supported by audit reports, but the buyer may still need expert interpretation of credibility. Environmental performance may include measurable energy use but also qualitative evidence about packaging redesign. Hybrid weights provide a disciplined way to combine these information types.

3.5 Fuzzy TOPSIS prioritization

After hybrid weights are obtained, the suppliers are ranked using fuzzy TOPSIS. The normalized weighted decision matrix is constructed by multiplying each supplier's normalized criterion value by the hybrid criterion weight. The positive ideal solution contains the best weighted value for each criterion, while the negative ideal solution contains the worst weighted value. Each supplier's distance to the positive and negative ideals is calculated. The final closeness coefficient is CCi = Di- / (Di+ + Di-), where Di+ is the distance to the positive ideal and Di- is the distance to the negative ideal.

A higher closeness coefficient indicates that the supplier is closer to the ideal supplier profile and farther from the weakest profile. This interpretation is understandable to managers because it describes both aspiration and avoidance. A supplier may not be the best in every criterion, but it can still rank highly if it is close to the ideal across the most important criteria. The model therefore supports balanced prioritization rather than a winner-takes-all rule based on one criterion. This is useful in food manufacturing because no supplier is likely to dominate every sustainability and resilience attribute.

To support transparency, the model reports not only the final ranking but also the criteria weights, dimension-level contributions, and sensitivity results. Procurement managers can therefore see why one supplier ranks higher than another. For example, a supplier may rank second because it performs strongly in environmental criteria but slightly weaker in recovery speed. Another supplier may rank third because it has strong resilience but less attractive packaging performance. Such explanations make the model useful for supplier development conversations.

3.6 Robustness and sensitivity analysis

Robustness analysis is necessary because supplier rankings can be sensitive to weights, normalization, and judgment uncertainty. Sensitivity analysis is conducted in three ways. First, alpha is varied to test whether the supplier ranking changes when subjective or objective weights dominate. Second, the dimension-level emphasis is adjusted to test scenarios such as carbon-focused procurement, safety-focused procurement, and resilience-focused procurement. Third, the effect of small perturbations in supplier scores is checked to identify whether the top ranking is stable or fragile.

The purpose of sensitivity analysis is not to eliminate managerial judgment. Instead, it clarifies where judgment matters. If two suppliers switch rank under a small weight change, managers should examine them as near-equivalent and perhaps assign them to different sourcing roles. If a supplier remains first across scenarios, it can be considered a robust strategic supplier. This interpretation follows supply chain risk management research that stresses the need to understand vulnerability and contingency rather than rely on a single deterministic plan (Tang, 2006).

4. Case Design and Data Construction

4.1 Case background

The case is built around a mid-sized food manufacturer in eastern China that produces frozen grain-based products, ready-to-cook meals, and packaged snack ingredients for regional retail channels. The company is not a global brand, but it has growing sustainability pressure from retailers and local regulators. It also experienced procurement interruptions during extreme weather and transport restrictions. The firm therefore wants to redesign its supplier evaluation process so that green performance and resilience are considered before annual framework contracts are renewed.

Six candidate suppliers are evaluated. They provide comparable ingredient and packaging-related inputs and are already qualified at the minimum compliance level. The question is not whether a supplier is legally acceptable, but which suppliers should receive priority for strategic sourcing, joint improvement projects, and backup capacity. This setting is realistic because many food manufacturers do not choose among completely unknown suppliers; they prioritize among pre-qualified suppliers with different strengths and weaknesses.

Table 4. Candidate supplier profiles

Supplier	Main role	Experience	Certification and green evidence	Resilience evidence
A1	Ingredient processor	18 years	ISO 22000; HACCP; local green factory documentation	Strong cold-chain monitoring and emergency production plan
A2	Grain material supplier	12 years	ISO 9001; food safety license; partial carbon data	Stable quality with moderate route redundancy
A3	Packaging and ingredient supplier	22 years	Green packaging certificate; ISO 22000	Good flexibility and multi-source input base
A4	Local agricultural processor	25 years	Food safety license; partial environmental audit	Low cost but weaker digital monitoring
A5	Integrated food material supplier	16 years	ISO 22000; recyclable packaging program; energy-saving records	Strong sustainability profile and good buffer stock
A6	Specialty	10 years	Food safety	Acceptable quality

See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2025.020401

	ingredient supplier		license; limited green documentation	but weaker resilience evidence

Table 4 summarizes the supplier profiles. The suppliers are anonymized because the purpose is to demonstrate the decision model rather than disclose proprietary commercial information. A1 and A5 show the strongest preliminary evidence, but they differ in their strengths. A1 has stronger food safety governance and recovery planning, while A5 has stronger green packaging and resource efficiency. A3 appears flexible and relatively balanced. A4 is attractive in cost terms but weaker in digital monitoring. A6 is acceptable as a transactional supplier but lacks evidence for strategic prioritization.

The case design is consistent with the idea that supplier selection should be embedded in relationship and development strategies. A supplier with a lower current rank is not automatically excluded. It may be used for non-critical materials or placed into a development program. Sustainable supplier management models emphasize that monitoring and development decisions should follow selection results (Zimmer et al., 2016). Therefore, the final ranking is interpreted as guidance for sourcing roles rather than as a simple acceptance or rejection list.

4.2 Expert panel and evaluation protocol

The expert panel includes six decision makers: one procurement manager, one quality assurance manager, one production planning supervisor, one logistics coordinator, one sustainability officer, and one external food safety consultant. Each expert has more than eight years of relevant experience. The panel first reviewed the criteria definitions, then discussed available supplier evidence, and finally assigned linguistic scores. The evaluation procedure was conducted in two rounds to reduce misunderstanding. In the first round, experts scored independently. In the second round, differences were discussed and aggregated scores were confirmed.

This group procedure is important because green supplier prioritization crosses functional boundaries. Procurement managers may emphasize cost and delivery, while sustainability officers may emphasize carbon and packaging. Food safety specialists may emphasize hazard analysis, traceability, and documentation. Logistics experts may emphasize recovery speed and route redundancy. A group decision process allows these perspectives to be represented explicitly. This is consistent with sustainable supply chain theory, which treats sustainability as a multi-stakeholder decision rather than a purely purchasing calculation (Ahi & Searcy, 2013).

The experts were instructed to evaluate actual performance evidence rather than supplier promises. For example, environmental certification had to be supported by valid documentation. Digital monitoring capability had to be supported by actual tracking, reporting, and exception management. Food safety governance had to be evaluated by audit results, recall records, and corrective-action routines. This evidence-based scoring reduces impression bias and makes the fuzzy evaluation more defensible in later supplier negotiations.

4.3 Data matrix and preliminary interpretation

The defuzzified scores show that A1 has consistently strong performance in food safety governance, recovery speed, buffer capacity, delivery reliability, and digital monitoring. A5 has strong environmental performance, particularly in energy and water efficiency and green packaging. A3 has relatively strong flexibility and multi-source adaptability. A2 is reliable but less distinctive in social and resilience criteria. A4 performs well on cost stability and local responsibility but weaker on delivery reliability and digital monitoring. A6 is generally acceptable but rarely leading. This pattern reflects the common procurement reality that suppliers have mixed rather than uniform profiles.

The data matrix also shows why single-criterion selection would be misleading. If the firm selected by cost stability only, A4 might appear attractive. If it selected by packaging readiness only, A5 might appear best. If it selected by recovery speed only, A1 would dominate. A multi-criteria model prevents these narrow conclusions by considering the full sustainability-resilience profile. This approach follows the broader green supplier selection literature, which emphasizes that environmental improvement must be balanced with operational feasibility (Lee et al., 2009).

The evaluation also illustrates the value of fuzzy scores. Experts did not claim exact knowledge of every supplier's carbon intensity or recovery speed. Instead, they used ranges that captured confidence and uncertainty. The final defuzzified scores are therefore not treated as laboratory measurements. They are structured representations of audited evidence and professional judgment. This distinction is important because decision models in procurement must remain honest about uncertainty rather than hide it behind excessive numerical precision.

4.4 Ethical and practical considerations

Supplier prioritization can affect business opportunities for suppliers, so the evaluation process should be transparent and fair. Criteria definitions should be shared with suppliers before the assessment cycle, and suppliers should be allowed to provide evidence. When suppliers receive lower scores, the buyer should provide actionable feedback rather than vague criticism. Sustainable supplier selection under attractive criteria has been discussed as a way to incorporate realistic managerial preferences while preserving systematic evaluation (Jain et al., 2020).

Food manufacturers should also avoid using the model to shift all sustainability responsibility to suppliers. The focal manufacturer must support improvement through training, stable contracts, forecasting information, and joint process redesign. Supplier performance is partly shaped by buyer behavior, especially when buyers demand low prices, short lead times, and frequent changes. The proposed model should therefore be interpreted as a decision-support and collaboration tool, not as a punitive scoring mechanism.

5. Results

5.1 Criteria weights

The hybrid weights indicate that resilience and social-food-safety criteria are the most influential dimensions in the case. Recovery speed receives the highest weight, followed by food safety governance, buffer capacity, multi-source adaptability, labor and welfare compliance, delivery reliability, information transparency, and digital monitoring capability. Environmental criteria remain important, but none of them dominates the model individually. This result suggests that the manufacturer considers green performance necessary but insufficient unless the supplier can also maintain safe and continuous supply.

Table 5. Subjective, objective, and hybrid criteria weights

Criterion	Dimension	Subjective	Objective	Hybrid
EC1	Economic	0.0550	0.0610	0.0577
EC2	Economic	0.0600	0.0570	0.0587
EC3	Economic	0.0620	0.0690	0.0652
EC4	Economic	0.0500	0.0460	0.0482
EN1	Environmental	0.0580	0.0640	0.0607
EN2	Environmental	0.0560	0.0550	0.0556
EN3	Environmental	0.0540	0.0490	0.0518
EN4	Environmental	0.0520	0.0480	0.0502
SO1	Social	0.0760	0.0730	0.0746
SO2	Social	0.0700	0.0660	0.0682
SO3	Social	0.0660	0.0630	0.0647
SO4	Social	0.0600	0.0550	0.0578
RE1	Resilience	0.0800	0.0780	0.0791
RE2	Resilience	0.0740	0.0710	0.0726
RE3	Resilience	0.0700	0.0720	0.0709
RE4	Resilience	0.0570	0.0730	0.0642

Table 5 shows that subjective and objective weights are similar for many criteria but diverge in meaningful ways. Delivery reliability and digital monitoring receive slightly higher objective weights because supplier scores vary more in those criteria. Food safety governance and recovery speed receive high subjective weights because experts view them as strategically critical for food manufacturing. This difference supports the use of hybrid weighting. A purely objective model would understate some strategic priorities, while a purely subjective model would underuse the information contained in supplier variation.

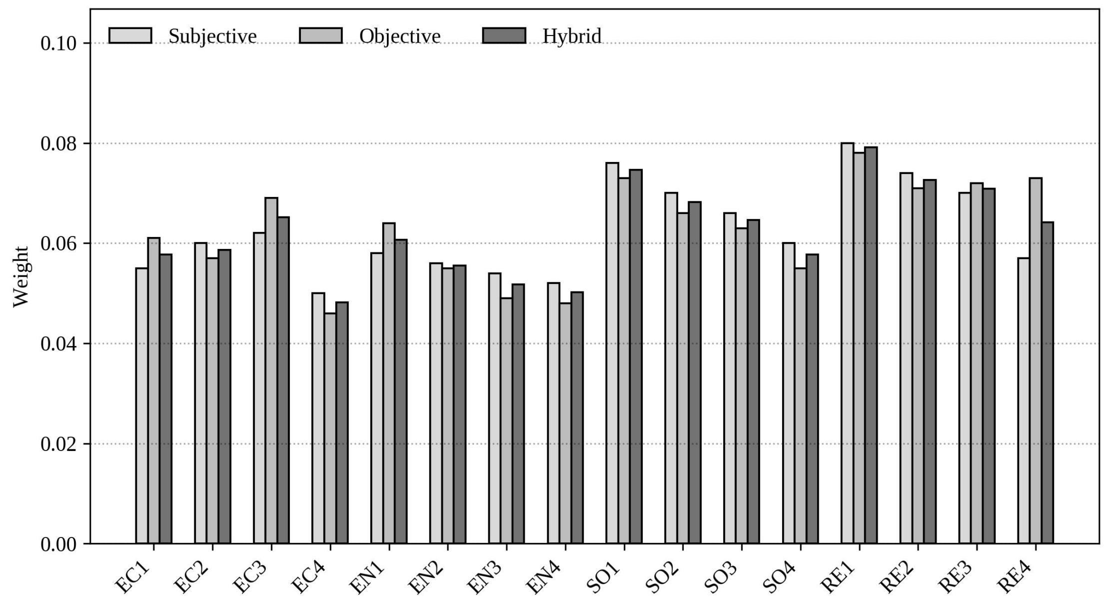


Figure 3. Subjective, objective, and hybrid weights of evaluation criteria

Figure 3 visualizes the three weight vectors. The pattern confirms that the model does not simply replicate expert preference or objective dispersion. Instead, it produces a balanced hybrid structure. Social and resilience criteria receive the highest combined importance because they connect safety, legitimacy, and continuity. Environmental criteria are still substantial, particularly carbon intensity and resource efficiency, but they are interpreted together with safety and recovery. This is consistent with research arguing that green supplier selection should integrate environmental practice with broader supply chain performance (Govindan et al., 2015).

The dimension-level aggregation provides further insight. Economic reliability accounts for roughly 23 percent of total importance, environmental performance for 22 percent, social and food-safety responsibility for 27 percent, and resilience for 28 percent. This distribution shows that the company does not abandon economic criteria, but it avoids allowing cost to dominate the decision. In food manufacturing, the cost of a supply disruption, recall, or public sustainability failure can exceed short-term purchasing savings. The weighting result therefore has strong managerial logic.

5.2 Supplier ranking

The fuzzy TOPSIS ranking identifies A1 as the highest-priority supplier. A1's advantage comes from its strong scores in recovery speed, food safety governance, delivery reliability, buffer capacity, and digital monitoring. A5 ranks second because it has the strongest environmental profile and a good resilience base, but it is slightly weaker than A1 in recovery speed and food safety governance. A3 ranks third because it is flexible and adaptable, though its environmental certification and buffer capacity are not as strong as those of A1 and A5. The remaining suppliers are acceptable but less suitable for strategic priority.

Table 6. Fuzzy TOPSIS supplier ranking

Supplier	Final fuzzy closeness	Rank	Suggested sourcing role
A1	8.3892	1	Strategic priority
A5	8.3095	2	Preferred backup
A3	8.0980	3	Development candidate
A2	7.9371	4	Development candidate
A4	7.8587	5	Transactional or improvement-needed
A6	7.5394	6	Transactional or improvement-needed

Table 6 translates the mathematical ranking into sourcing roles. A1 is recommended as the strategic priority supplier. A5 is recommended as a preferred backup or dual-sourcing partner, particularly for product lines where green packaging and resource efficiency are important. A3 is suitable for flexible support and contingency use. A2 can be retained as a stable supplier but should improve transparency and resilience documentation. A4 and A6 should be used carefully unless they improve digital monitoring, environmental evidence, and recovery planning.

The closeness difference between A1 and A5 is not large, which means that both suppliers should remain in the strategic supplier pool. This is important because resilience is strengthened by avoiding excessive dependence on a single supplier. Dual sourcing can improve continuity, but it should not be based on random diversification. It should combine suppliers with complementary strengths. In this case, A1 offers stronger safety-resilience performance, while A5 offers stronger green performance. Together they create a more balanced supplier portfolio.

A3's position is managerially interesting. It does not lead in the highest-weighted criteria, but it performs consistently across flexibility and multi-source adaptability. Such a supplier can be valuable during demand shifts or material substitution. The result suggests that the manufacturer should not evaluate A3 only by its final rank. It may be a useful contingency partner for product lines that require material flexibility. Supplier prioritization is therefore more useful when ranking is connected to sourcing role design.

The lower ranking of A4 does not imply that it has no value. A4 has cost and local responsibility advantages, but weak digital monitoring and lower delivery reliability reduce its strategic position. If the manufacturer wants to support local suppliers, A4 can be included in a development program focused on traceability, environmental documentation, and logistics planning. This interpretation aligns with sustainable supply chain management research that encourages supplier development rather than simple supplier replacement (Walker et al., 2008).

A6 ranks last because it has no strong advantage in the highest-weighted criteria. It may still be used for non-critical materials or short-term orders, but it should not be treated as a strategic supplier until it improves documentation, monitoring, and recovery capability. This ranking helps managers allocate attention. Instead of spreading supplier development resources equally across all suppliers, the company can focus on improving near-strategic suppliers and managing lower-ranked suppliers through risk controls.

5.3 Sensitivity analysis

The first sensitivity test varies the subjective-weight share alpha from 0 to 1. A1 remains first across all tested values, and A5 remains second. This result indicates that the top ranking is robust to the balance between expert preference and objective variation. A3 and A2 occasionally move closer to each other, which means their relative position is more sensitive. A4 and A6 remain lower-ranked under all scenarios. This stability supports the model's practical reliability.

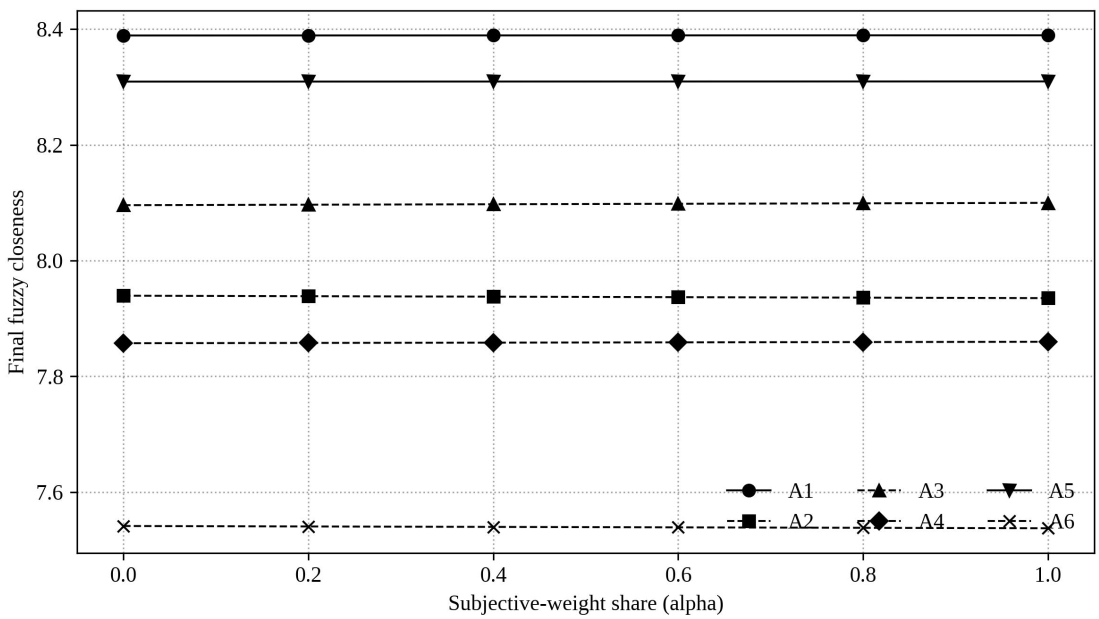


Figure 4. Sensitivity of supplier scores to subjective-weight share

Figure 4 shows the sensitivity trajectories. The top two suppliers have parallel and consistently high closeness scores. The middle suppliers show smaller gaps, suggesting that procurement managers should consider additional business constraints such as capacity, contract terms, and product category fit when choosing between them. The stability of A1 and A5 is important because it allows managers to proceed with strategic negotiations without worrying that a small weight adjustment would reverse the decision.

The second sensitivity test changes dimension emphasis. In a carbon-focused scenario, A5 moves closer to A1 because its environmental scores are stronger. In a safety-focused scenario, A1 extends its lead due to food safety governance. In a resilience-focused scenario, A1 also remains first, while A3 improves because of multi-source adaptability. In a cost-focused scenario, A4 improves but does not reach the top because weaker digital monitoring and delivery reliability create offsetting disadvantages. These scenarios show that the model supports strategic discussion rather than mechanical ranking.

The third test perturbs supplier scores by plus or minus five percent to simulate audit uncertainty. A1 remains first in most perturbation runs, and A5 remains within the top two. A3 and A2 exchange rank in some runs, which confirms that they should be treated as close competitors. The result also shows that the model is not excessively sensitive to small score changes. This matters because fuzzy supplier evaluation is inherently uncertain. A model that changes dramatically under minor perturbation would be difficult to defend in a procurement committee.

5.4 Comparison with simple scoring

A comparison with a simple equal-weight average shows why hybrid fuzzy prioritization is useful. Under equal weights, A5 can appear nearly tied with A1 because its environmental performance is very strong. Under the hybrid model, A1 gains an advantage because food safety governance and recovery speed receive higher weights. This difference does not mean that the equal-weight result is wrong; rather, it shows that the hybrid model better reflects the company's strategic priorities. Equal weighting is transparent but rarely realistic in safety-sensitive food manufacturing.

A comparison with a cost-focused scoring rule also produces a different conclusion. A4 looks attractive if cost stability receives dominant emphasis. However, its weak digital monitoring and delivery reliability make it risky as a strategic supplier. This result supports the argument that green supplier prioritization should resist narrow purchasing logic. Green procurement is not merely buying at a lower price with greener documentation; it is the design of reliable, responsible, and adaptive supply relationships.

The comparison also highlights the difference between supplier selection and supplier prioritization. Selection asks which supplier should be chosen. Prioritization asks how suppliers should be arranged in a portfolio of strategic, backup, developmental, and transactional roles. Food manufacturers often need more than one supplier because continuity and product variety require sourcing flexibility. The proposed model supports this broader portfolio interpretation, which is more suitable for resilience-oriented procurement.

6. Discussion

6.1 Theoretical implications

The first theoretical implication is that green supplier selection in food manufacturing should be reframed as sustainability-resilience prioritization. Environmental performance is essential, but it cannot be evaluated apart from food safety and disruption recovery. This reframing responds to the broader sustainable supply chain literature, which calls for integrated economic, environmental, and social thinking (Srivastava, 2007). The present study extends that logic by adding resilience as an explicit dimension rather than treating it as a hidden operational factor.

The second implication concerns the role of digital capability. Digital monitoring is not treated as a separate technological objective but as a contributor to resilience and transparency. Research on blockchain and Industry 4.0 suggests that digital technologies can improve information integration, traceability, and process coordination (Chen et al., 2024). However, the results show that digital capability must be combined with food safety governance and recovery planning. Technology without organizational routines does not guarantee supplier quality.

The third implication is methodological. Hybrid weighting provides a way to reconcile managerial priorities with data-driven contrast. This is important because supplier evaluation is neither purely subjective nor purely objective. Procurement teams have strategic goals, but supplier data reveal where differences actually exist. The proposed model shows how both sources can be integrated without hiding the assumptions. This contributes to MCDM research by emphasizing explainability and auditability, not just ranking accuracy.

The fourth implication is that fuzzy evaluation remains valuable even in an era of big data and AI. Advanced analytics can process more data, but many supplier attributes remain partially qualitative. For example, transparency, labor compliance, and recovery culture cannot be fully captured by sensor data. Research on artificial intelligence shows that data-driven models are increasingly powerful, yet business decision-making still requires contextual interpretation (Zhang & Lu, 2021). Fuzzy models can bridge expert interpretation and structured calculation.

6.2 Managerial implications

For procurement managers, the model provides a practical process for turning sustainability and resilience goals into supplier priorities. The criteria system can be incorporated into annual supplier review, new supplier qualification, and strategic sourcing committees. The weights can be adjusted to match product category, regulatory pressure, and company strategy. For example, fresh dairy inputs may require higher emphasis on cold-chain resilience, while packaging suppliers may require higher emphasis on recyclability and carbon documentation.

For sustainability managers, the results show how green criteria can be defended within a broader business decision. Environmental criteria often lose influence when they are presented as separate compliance indicators. In the hybrid model, they are connected to cost stability, quality, safety, and resilience. This makes the sustainability argument more operationally credible. The model can also identify which suppliers need targeted improvement in packaging, certification, carbon measurement, or resource efficiency.

For quality and food safety managers, the model demonstrates that safety governance should be a central supplier criterion. Food safety is not just a minimum qualification; it is a differentiating capability that influences strategic supplier status. A supplier with excellent quality systems reduces recall risk and protects consumer trust. The high weight of food safety governance in the case indicates that green supplier prioritization in food manufacturing must remain safety-centered.

For logistics and risk managers, the model supports dual sourcing and backup design. Instead of choosing backup suppliers based only on low price or geographic proximity, managers can identify suppliers with complementary resilience strengths. A5, for example, is not ranked first but is a strong backup because it combines green performance with adequate buffer capacity. A3 offers flexibility and multi-source adaptability. These insights support a more nuanced sourcing portfolio.

For suppliers, the model provides clearer development signals. A supplier can see whether it loses priority because of weak environmental evidence, limited monitoring, insufficient buffer capacity, or poor transparency. This supports constructive improvement discussions. Supplier development is more effective when feedback is specific and linked to future business opportunity. The model can therefore improve buyer-supplier communication rather than simply impose a score.

6.3 Digital governance and implementation

Implementation should begin with data governance. The manufacturer must define evidence requirements for each criterion, such as audit records, certification documents, carbon estimates, delivery logs, incident reports, and recovery plans. Where data are unavailable, fuzzy expert judgment can be used, but the absence of data should be recorded. Over time, the company can replace some fuzzy judgments with measured indicators. This staged approach is realistic for medium-sized food manufacturers.

Blockchain and IoT can strengthen implementation by improving traceability and data integrity. Research on blockchain technology identifies decentralization, immutability, and transparency as features that can support trusted information sharing (Lu, 2019b). Research on blockchain-IoT integration also shows that connected systems can support secure data exchange across industrial networks (Xu et al., 2021). Nevertheless, the company should evaluate whether digital tools improve the actual supplier criteria rather than adopting technology for symbolic reasons.

The model can also be embedded in a management analytics dashboard. A dashboard could show supplier scores, criteria weights, ranking changes, risk alerts, and improvement plans. Management analytics research emphasizes that structured analytics can support decision-making when it connects data, managerial interpretation, and business action (Lu, 2021). In the supplier context, the dashboard should make weighting assumptions visible and allow scenario analysis rather than present a single unexplained ranking.

Cybersecurity and data reliability should be included in implementation planning. If supplier data are transmitted through digital systems, the buyer must evaluate data access, device security, and system continuity. Research on IoT cybersecurity warns that connected systems can introduce new vulnerabilities if security is not designed into the architecture (Lu & Xu, 2019). Supplier prioritization should therefore consider digital monitoring as a capability that requires governance, not as a risk-free advantage.

6.4 Limitations and future research

This study has limitations. First, it uses a single case setting and simulated anonymized supplier data based on a realistic food manufacturing scenario. Future research can apply the model to actual multi-company datasets and compare results across product categories. Second, the model uses triangular fuzzy numbers. Other fuzzy environments, such as intuitionistic or Pythagorean fuzzy sets, could represent hesitation in richer ways. Third, the ranking model is static. Future work can extend the model to multi-period supplier evaluation, order allocation, and contract design.

A second future direction is to integrate life-cycle assessment data with supplier scoring. Environmental criteria in this study are evaluated at a procurement decision level. More detailed carbon, water, and packaging data could strengthen the environmental side of the model. However, such data must be standardized across suppliers to avoid unfair comparison. Future research can combine life-cycle indicators with fuzzy decision weights to build a stronger bridge between environmental accounting and procurement decision-making.

A third direction is to connect supplier prioritization with AI-based prediction. Machine learning models can forecast delivery delays, quality deviations, or supplier disruption likelihood. Yet prediction should be paired with interpretable decision rules. Research on Industry 4.0 and management analytics suggests that data-driven systems create value when they are embedded in managerial routines (Lu, 2025). Future models can combine predictive supplier risk scores with fuzzy multi-criteria prioritization.

A final direction is behavioral. Supplier prioritization models affect negotiations, trust, and perceptions of fairness. Suppliers may cooperate when they believe the model is transparent and improvement-oriented, but resist when they view it as arbitrary. Future research can examine how evaluation transparency influences supplier motivation and how buyers can use prioritization results to support collaborative sustainability improvement.

Table 7. Managerial implications of the ranking results

Function	Key action	Expected value
Procurement	Use A1 as strategic priority and A5 as green-resilience backup	Build sourcing portfolio instead of single-winner sourcing
Sustainability	Track carbon, energy-water efficiency, packaging, and certification evidence	Connect green goals with supplier development
Food safety	Treat safety governance as a differentiating supplier capability	Link supplier priority to recall prevention and consumer protection
Logistics and risk	Use recovery speed, buffers, and route adaptability in contract review	Reduce disruption exposure and waste from emergency sourcing
Digital governance	Require traceability and monitoring evidence, not platform claims	Improve data quality and auditability

7. Conclusion

This study proposed a hybrid fuzzy decision model for green supplier prioritization in food manufacturing. The model integrates sustainability and resilience criteria, converts linguistic expert judgments into fuzzy values, combines subjective and objective weighting, and ranks suppliers using fuzzy TOPSIS. The case demonstration shows that recovery speed, food safety governance, buffer capacity, multi-source adaptability, and labor and welfare compliance are central criteria. A1 ranks first, followed by A5 and A3. Sensitivity analysis confirms that the top two suppliers remain stable across changes in the subjective-objective weighting balance.

The main conclusion is that green supplier prioritization should not be reduced to environmental documentation. In food manufacturing, a green supplier must also be safe, transparent, reliable, and resilient. Environmental criteria remain essential, but they must be evaluated together with food safety governance and disruption recovery. This integrated view is especially important for medium-sized food manufacturers that face increasing sustainability pressure but cannot build overly complex decision systems.

The proposed model has practical value because it is transparent and adjustable. Managers can change criteria, weights, or scenario assumptions without abandoning the structure. The outputs support strategic supplier selection, backup sourcing, supplier development, and procurement committee discussion. The model also supports communication with suppliers because it identifies specific improvement areas rather than offering only a final score.

Future research can validate the model using real longitudinal supplier data, integrate more precise environmental accounting, and connect fuzzy prioritization with predictive analytics. As food supply chains become more digital, more exposed to disruption, and more accountable for sustainability outcomes, supplier prioritization will become a core management analytics task. A hybrid fuzzy model offers a practical path for turning complex sustainability-resilience concerns into responsible sourcing decisions.

Declarations

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability Statement: The illustrative data used in the case demonstration are anonymized and constructed for methodological demonstration. Additional calculation tables can be made available upon reasonable request.

Author Contributions: Conceptualization, M.C. and L.T.; methodology, M.C. and R.W.; data curation, Y.Z. and R.W.; writing - original draft, M.C. and Y.Z.; writing - review and editing, R.W. and L.T.; supervision, L.T.

Reference

Ageron, B., Gunasekaran, A., & Spalanzani, A. (2012). Sustainable supply management: An empirical study. International Journal of Production Economics, 140(1), 168-182. https://doi.org/10.1016/j.ijpe.2011.04.007

Ahi, P., & Searcy, C. (2013). A comparative literature analysis of definitions for green and sustainable supply chain management. Journal of Cleaner Production, 52, 329-341. https://doi.org/10.1016/j.jclepro.2013.02.018

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. Fuzzy Sets and Systems, 20(1), 87-96. https://doi.org/10.1016/S0165-0114(86)80034-3

Bai, C., & Sarkis, J. (2010). Integrating sustainability into supplier selection with grey system and rough set methodologies. International Journal of Production Economics, 124(1), 252-264. https://doi.org/10.1016/j.ijpe.2009.11.023

Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. Management Science, 17(4), B141-B164. https://doi.org/10.1287/mnsc.17.4.B141

Beske, P., Land, A., & Seuring, S. (2014). Sustainable supply chain management practices and dynamic capabilities in the food industry: A critical analysis of the literature. International Journal of Production Economics, 152, 131-143. https://doi.org/10.1016/j.ijpe.2013.12.026

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. European Journal of Operational Research, 233(2), 299-312. https://doi.org/10.1016/j.ejor.2013.09.032

Büyüközkan, G., & Çifçi, G. (2011). A novel fuzzy multi-criteria decision framework for sustainable supplier selection with incomplete information. Computers in Industry, 62(2), 164-174. https://doi.org/10.1016/j.compind.2010.10.009

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. International Journal of Physical Distribution & Logistics Management, 38(5), 360-387. https://doi.org/10.1108/09600030810882816

Chai, J., Liu, J. N. K., & Ngai, E. W. T. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. Expert Systems with Applications, 40(10), 3872-3885. https://doi.org/10.1016/j.eswa.2012.12.040

Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets and Systems, 114(1), 1-9. https://doi.org/10.1016/S0165-0114(97)00377-1

Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. International Journal of Production Economics, 102(2), 289-301. https://doi.org/10.1016/j.ijpe.2005.03.009

Chen, Y., Lu, Y., Bulysheva, L., & Kataev, M. Y. (2024). Applications of blockchain in Industry 4.0: A review. Information Systems Frontiers, 26(5), 1715-1729. https://doi.org/10.1007/s10796-022-10248-7

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. The International Journal of Logistics Management, 15(2), 1-14. https://doi.org/10.1108/09574090410700275

Dania, W. A. P., Xing, K., & Amer, Y. (2018). Collaboration behavioural factors for sustainable agri-food supply chains: A systematic review. Journal of Cleaner Production, 186, 851-864. https://doi.org/10.1016/j.jclepro.2018.03.148

Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The CRITIC method. Computers & Operations Research, 22(7), 763-770. https://doi.org/10.1016/0305-0548(94)00059-H

Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. Journal of Cleaner Production, 47, 345-354. https://doi.org/10.1016/j.jclepro.2012.04.014

Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. Journal of Cleaner Production, 98, 66-83. https://doi.org/10.1016/j.jclepro.2013.06.046

Grimm, J. H., Hofstetter, J. S., & Sarkis, J. (2014). Critical factors for sub-supplier management: A sustainable food supply chains perspective. International Journal of Production Economics, 152, 159-173. https://doi.org/10.1016/j.ijpe.2013.12.011

Handfield, R., Walton, S. V., Sroufe, R., & Melnyk, S. A. (2002). Applying environmental criteria to supplier assessment: A study in the application of the Analytical Hierarchy Process. European Journal of Operational Research, 141(1), 70-87. https://doi.org/10.1016/S0377-2217(01)00261-2

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. European Journal of Operational Research, 202(1), 16-24. https://doi.org/10.1016/j.ejor.2009.05.009

Hohenstein, N. O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience: A systematic review and paths for further investigation. International Journal of Physical Distribution & Logistics Management, 45(1/2), 90-117. https://doi.org/10.1108/IJPDLM-05-2013-0128

Ivanov, D. (2020). Viable supply chain model: Integrating agility, resilience and sustainability perspectives. International Journal of Production Research, 58(10), 2904-2915. https://doi.org/10.1080/00207543.2020.1750727

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. International Journal of Production Research, 57(3), 829-846. https://doi.org/10.1080/00207543.2018.1488086

Jain, N., Singh, A. R., & Upadhyay, R. K. (2020). Sustainable supplier selection under attractive criteria through FIS and integrated fuzzy MCDM techniques. International Journal of Sustainable Engineering, 13(6), 441-462. https://doi.org/10.1080/19397038.2020.1737751

Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience. International Journal of Production Economics, 171, 116-133. https://doi.org/10.1016/j.ijpe.2015.10.023

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. Process Safety and Environmental Protection, 117, 408-425. https://doi.org/10.1016/j.psep.2018.05.009

Kamble, S. S., Gunasekaran, A., & Sharma, R. (2020). Modeling the blockchain enabled traceability in agriculture supply chain. International Journal of Information Management, 52, 101967. https://doi.org/10.1016/j.ijinfomgt.2019.05.023

Kannan, D., Jabbour, A. B. L. S., & Jabbour, C. J. C. (2014). Selecting green suppliers based on GSCM practices: Using fuzzy TOPSIS applied to a Brazilian electronics company. European Journal of Operational Research, 233(2), 432-447. https://doi.org/10.1016/j.ejor.2013.07.023

Kersuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). Journal of Business Economics and Management, 11(2), 243-258. https://doi.org/10.3846/jbem.2010.12

Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E. K., & Antucheviciene, J. (2017). Supplier evaluation and selection in fuzzy environments: A review of MADM approaches. Economic Research-Ekonomska Istraživanja, 30(1), 1073-1118. https://doi.org/10.1080/1331677X.2017.1314828

Kouhizadeh, M., Saberi, S., & Sarkis, J. (2021). Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. International Journal of Production Economics, 231, 107831. https://doi.org/10.1016/j.ijpe.2020.107831

Kuo, R. J., Wang, Y. C., & Tien, F. C. (2010). Integration of artificial neural network and MADA methods for green supplier selection. Journal of Cleaner Production, 18(12), 1161-1170. https://doi.org/10.1016/j.jclepro.2010.03.020

Lee, A. H. I., Kang, H. Y., Hsu, C. F., & Hung, H. C. (2009). A green supplier selection model for high-tech industry. Expert Systems with Applications, 36(4), 7917-7927. https://doi.org/10.1016/j.eswa.2008.11.052

Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. Journal of Industrial Information Integration, 6, 1-10. https://doi.org/10.1016/j.jii.2017.04.005

Lu, Y. (2019). Artificial intelligence: A survey on evolution, models, applications and future trends. Journal of Management Analytics, 6(1), 1-29. https://doi.org/10.1080/23270012.2019.1570365

Lu, Y. (2019). The blockchain: State-of-the-art and research challenges. Journal of Industrial Information Integration, 15, 80-90. https://doi.org/10.1016/j.jii.2019.04.002

Lu, Y. (2021). Technological innovation and the emergence of a new interdisciplinary field: Management Analytics. Nanotechnologies in Construction, 13(3), 181-192. https://doi.org/10.15828/2075-8545-2021-13-3-181-192

Lu, Y. (2022). Implementing blockchain in information systems: A review. Enterprise Information Systems, 16(12), 1876-1907. https://doi.org/10.1080/17517575.2021.2008513

Lu, Y. (2025). The current status and developing trends of Industry 4.0: A review. Information Systems Frontiers, 27(1), 215-234. https://doi.org/10.1007/s10796-021-10221-w

Lu, Y., & Xu, L. D. (2019). Internet of Things (IoT) cybersecurity research: A review of current research topics. IEEE Internet of Things Journal, 6(2), 2103-2115. https://doi.org/10.1109/JIOT.2018.2869847

Lu, Y., Ivanov, L. A., Wang, F., Pisarenko, Z. V., & Ye, C. (2024). Management analytics: A bibliometric analysis. Nanotechnologies in Construction, 16(3), 257-266. https://doi.org/10.15828/2075-8545-2024-16-3-257-266

Mardani, A., Jusoh, A., Nor, K. M. D., Khalifah, Z., Zakwan, N., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications: A review of the literature from 2000 to 2014. Economic Research-Ekonomska Istraživanja, 28(1), 516-571. https://doi.org/10.1080/1331677X.2015.1075139

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445-455. https://doi.org/10.1016/S0377-2217(03)00020-1

Pagell, M., & Wu, Z. (2009). Building a more complete theory of sustainable supply chain management using case studies of ten exemplars. Journal of Supply Chain Management, 45(2), 37-56. https://doi.org/10.1111/j.1745-493X.2009.03162.x

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: Development of a conceptual framework. Journal of Business Logistics, 31(1), 1-21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x

Phochanikorn, P., & Tan, C. (2019). A new extension to a multi-criteria decision-making model for sustainable supplier selection under an intuitionistic fuzzy environment. Sustainability, 11(19), 5413. https://doi.org/10.3390/su11195413

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. The International Journal of Logistics Management, 20(1), 124-143. https://doi.org/10.1108/09574090910954873

Queiroz, M. M., Telles, R., & Bonilla, S. H. (2019). Blockchain and supply chain management integration: A systematic review of the literature. Supply Chain Management: An International Journal, 25(2), 241-254. https://doi.org/10.1108/SCM-03-2018-0143

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. Omega, 53, 49-57. https://doi.org/10.1016/j.omega.2014.11.009

Rezaei, J. (2016). Best-worst multi-criteria decision-making method: Some properties and a linear model. Omega, 64, 126-130. https://doi.org/10.1016/j.omega.2015.12.001

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. International Journal of Production Research, 57(7), 2117-2135. https://doi.org/10.1080/00207543.2018.1533261

Sarkis, J. (2003). A strategic decision framework for green supply chain management. Journal of Cleaner Production, 11(4), 397-409. https://doi.org/10.1016/S0959-6526(02)00062-8

Sarkis, J., Zhu, Q., & Lai, K. H. (2011). An organizational theoretic review of green supply chain management literature. International Journal of Production Economics, 130(1), 1-15. https://doi.org/10.1016/j.ijpe.2010.11.010

Scholten, K., & Schilder, S. (2015). The role of collaboration in supply chain resilience. Supply Chain Management: An International Journal, 20(4), 471-484. https://doi.org/10.1108/SCM-11-2014-0386

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production, 16(15), 1699-1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Shen, L., Olfat, L., Govindan, K., Khodaverdi, R., & Diabat, A. (2013). A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences. Resources, Conservation and Recycling, 74, 170-179. https://doi.org/10.1016/j.resconrec.2012.09.006

Srivastava, S. K. (2007). Green supply-chain management: A state-of-the-art literature review. International Journal of Management Reviews, 9(1), 53-80. https://doi.org/10.1111/j.1468-2370.2007.00202.x

Tang, C. S. (2006). Perspectives in supply chain risk management. International Journal of Production Economics, 103(2), 451-488. https://doi.org/10.1016/j.ijpe.2005.12.006

Tsolakis, N. K., Keramydas, C. A., Toka, A. K., Aidonis, D. A., & Iakovou, E. T. (2014). Agrifood supply chain management: A comprehensive hierarchical decision-making framework and a critical taxonomy. Biosystems Engineering, 120, 47-64. https://doi.org/10.1016/j.biosystemseng.2013.10.014

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. International Journal of Production Research, 53(18), 5592-5623. https://doi.org/10.1080/00207543.2015.1037934

Verdouw, C. N., Wolfert, J., Beulens, A. J. M., & Rialland, A. (2016). Virtualization of food supply chains with the Internet of Things. Journal of Food Engineering, 176, 128-136. https://doi.org/10.1016/j.jfoodeng.2015.11.009

Walker, H., Di Sisto, L., & McBain, D. (2008). Drivers and barriers to environmental supply chain management practices: Lessons from the public and private sectors. Journal of Purchasing and Supply Management, 14(1), 69-85. https://doi.org/10.1016/j.pursup.2008.01.007

Wang, Y., Wang, W., Wang, Z., Deveci, M., Roy, S. K., & Kadry, S. (2024). Selection of sustainable food suppliers using the Pythagorean fuzzy CRITIC-MARCOS method. Information Sciences, 664, 120326. https://doi.org/10.1016/j.ins.2024.120326

Xu, L. D., Lu, Y., & Li, L. (2021). Embedding blockchain technology into IoT for security: A survey. IEEE Internet of Things Journal, 8(13), 10452-10473. https://doi.org/10.1109/JIOT.2021.3060508

Yildizbasi, A., & Arioz, Y. (2022). Green supplier selection in new era for sustainability: A novel method for integrating big data analytics and a hybrid fuzzy multi-criteria decision making. Soft Computing, 26, 253-270. https://doi.org/10.1007/s00500-021-06477-8

Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zhang, C., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. Journal of Industrial Information Integration, 23, 100224. https://doi.org/10.1016/j.jii.2021.100224

Zhu, Q., Sarkis, J., & Lai, K. H. (2008). Confirmation of a measurement model for green supply chain management practices implementation. International Journal of Production Economics, 111(2), 261-273. https://doi.org/10.1016/j.ijpe.2006.11.029

Zimmer, K., Fröhling, M., & Schultmann, F. (2016). Sustainable supplier management - a review of models supporting sustainable supplier selection, monitoring and development. International Journal of Production Research, 54(5), 1412-1442. https://doi.org/10.1080/00207543.2015.1079340