




An integrated decision-making approach for identifying sustainable tier-1 suppliers: Fuzzy Delphi-Borda-SWARA

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Abstract

Outsourcing has emerged as a key strategic approach for many organizations and manufacturers, leading to the creation of complex multi-tiered supplier networks. Efficient Supplier Network Management (SNM) is necessary, as every element within the network can significantly influence the final product's quality and delivery timeline. Among the strategies employed in SNM, the tiering of suppliers holds particular prominence, with tier-1 suppliers assuming a pivotal role in ensuring high-quality products and timely delivery. However, despite the criticality of tier-1 supplier selection, existing literature lacks comprehensive frameworks, specifically addressing the specification and prioritization of influential criteria in this context. This study addresses this gap by identifying and integrating key attributes of sustainable tier-1 suppliers through a meticulous review of the literature and expert panel consultations, followed by developing and categorizing a comprehensive list of criteria. A hybrid model is built up to determine criteria weights and relative importance values, employing Multi-Attribution Decision-Making (MADM) techniques; i.e., fuzzy Delphi, Borda, Step-wise Weight Assessment Ratio Analysis (SWARA). The model is then applied to an Iranian spare parts supplier, revealing key criteria for sustainable tier-1 supplier selection wherein “proper manufacturing and supply capabilities” is the most critical one. It is worth noting that this model is applicable across various industries beyond automotive. These criteria form the foundation of an efficient assessment framework designed specifically for tier-1 suppliers. Using the fuzzy Delphi, we identify 35 critical parameters influencing tier-1 supplier selection, from which the 10 most critical ones are specified and prioritized. These 10 criteria are also weighted using the Borda and SWARA methods. A comparative analysis is then conducted between the proposed model and the well-known MADM model in order to appraise the robustness and reliability. Additionally, Principal Component Analysis (PCA) and K-Means clustering methods are employed to uncover hidden patterns and groupings among the criteria based on expert evaluations. These insights further enhance the interpretability and decision-support capacity of the framework.

Keywords Sustainable supplier selection · Tier-1 suppliers · MADM · Fuzzy Delphi · Borda · SWARA

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1 Introduction

The importance of Supplier Network Management (SNM) arises from the fact that each component of the supply chain can influence the quality and delivery time of the final product, and outsourcing is a significant instrument for SNM that is performed with the purpose of work specialization. Under the framework of an Original Equipment Manufacturer (OEM) strategy, outsourced supply operation delineates three distinct categories of outsourced parts: black box, concurrent engineering, and co-design parts (Volpato, 2004). Irrespective of the chosen outsourcing model, a central challenge in manufacturing lies in identifying suitable entities for delegating parts production and assembly responsibilities. In scenarios characterized by the procurement of black box parts, transactions typically occur without any strategic buyer–seller relationship. Conversely, in the cases of concurrent engineering and co-design parts, the supplier's capabilities assume paramount importance, with the OEM seeking reliable partners capable of sustaining prolonged engagements in supply activities.

Helper and Henderson (2014) asserted that by 2008, purchased components accounted for about 70% of General Motors' (GM) total cost when the company outsourced its production processes. Nearly 70% of the value of automotive parts within GM is attributed to major suppliers lacking direct management affiliations. This underscores the inevitability of outsourcing for organizational expansion, a trend increasingly embraced by leading global corporations. This strategic shift is not driven by desperation but rather stems from the perceived advantages inherent in outsourcing endeavors that companies seek to leverage. However, a significant challenge associated with outsourcing initiatives lies in establishing robust relationships with a multitude of capable suppliers. GM, for instance, grapples with a diverse array of products, necessitating engagement with a varied spectrum of suppliers in the market for materials and components (Barra & Stevens, 2015). This is further exemplified by GM's extensive network of approximately 18,500 suppliers worldwide, catering to diverse material needs, component requirements, product assemblies, and systems (DSV, 2013).

One effective strategy for mitigating challenges between suppliers and OEMs is supplier tiering. Tiering is adopted for several reasons, notably to improve supply chain efficiency and simplify supplier management (Shin et al., 2000). Many prominent organizations such as Xerox, Chrysler, IBM, and Sun Microsystems have adopted tiering to manage their direct suppliers more effectively. Figure 1 provides an illustrative depiction of suppliers for Honda Accord parts, showcasing eight tier-1 suppliers, fifteen tier-2 suppliers, two tier-3 suppliers, and one tier-4 supplier in conjunction with Honda Motor Company serving as the OEM.

While tiered supply systems have gained traction among major corporations, particularly within the automotive sector, comprehensive research delineating and prioritizing assessment criteria for tiering decisions remains scant. Choi and Hartley (1996), in the early days when the topics of supplier tiering and selection were first being discussed, stated that there was no clear distinction between direct and indirect suppliers. Therefore, it appeared necessary at that time to propose criteria specifically for the selection of tier-1 suppliers. Even now, after many years, this issue remains open for discussion. The difference between then and now lies in the fact that today, growing attention to sustainability in supply chains has become the main motivation for addressing this topic. Although the motivations may differ over time, the identification of supplier selection criteria continues to receive significant

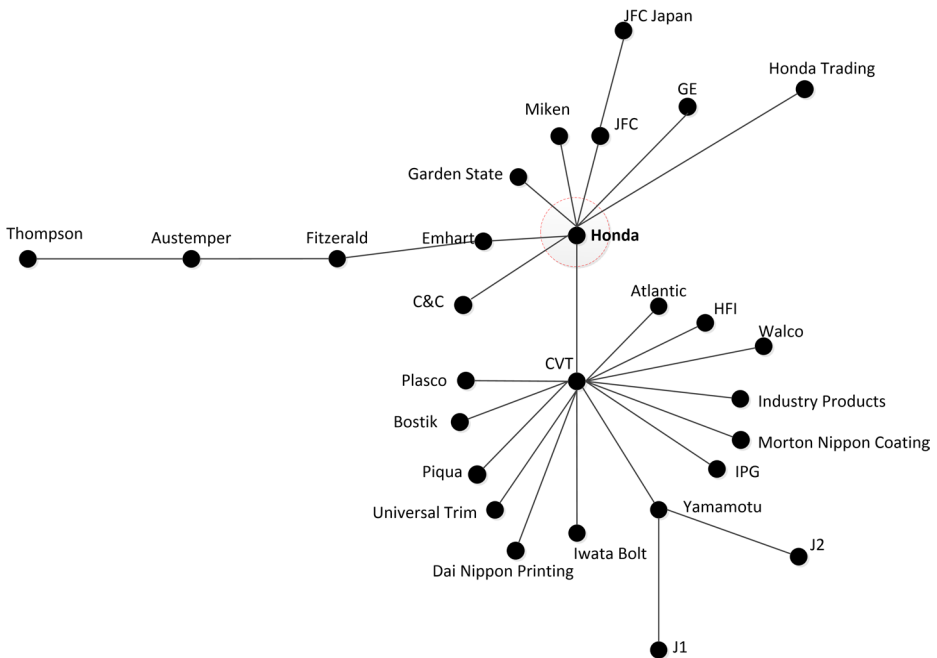


Fig. 1 Tiering Honda Accord suppliers; product-based model (Kim et al., 2011)

attention from industry practitioners, researchers, and supply chain managers, and has not lost its importance over time.

Despite variances in descriptions of supplier tiering and the absence of a universally accepted standard definition, scholars generally converge on the characterization of tier-1 suppliers. Most proposed definitions underscore a direct association between OEMs and tier-1 suppliers, irrespective of their role in providing final product components. Consequently, tier-1 suppliers occupy a proximate position preceding the OEM in the supply chain. Figure 2 illustrates a typical supply chain featuring supplier tiering (Lambert et al., 1998). Supplier tiering does not necessarily eliminate the occurrence of inter-tier relationships that are not in direct succession. As Lambert (2008) stated, hierarchical relationships among suppliers may deviate at higher tiers; for instance, tier-4 suppliers may establish direct connections with tier-2 suppliers.

Multi-Attribute Decision-Making (MADM) methods are recognized as potent models for ascertaining criteria weights and priorities, given the plethora of criteria and the intricacies inherent in decision-making processes (Martino Neto et al., 2023; Zhang et al., 2024). Accordingly, the present study endeavors to identify and quantify the weights and relative importance of each parameter influencing the sustainable tier-1 supplier selection process utilizing MADM techniques. Initially, a comprehensive list of assessment attributes is formulated through a review of relevant literature. Subsequently, the fuzzy Delphi method is employed to distill the most significant criteria based on expert opinions. Concurrently, the Step-wise Weight Assessment Ratio Analysis (SWARA) technique is utilized to rank and assign weights to criteria, elucidating the perspective of decision-makers in the context of the proposed case study research.

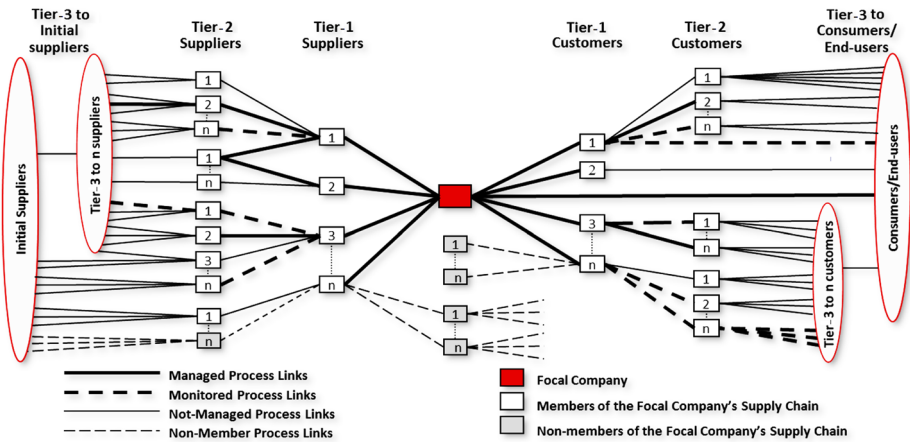


Fig. 2 Relationships among non-consecutive tiers (Lambert, 2008)

Although earlier works (e.g., Manello & Calabrese, 2019) examine supplier tiering in relation to cost and responsiveness, they do not integrate sustainability into a structured hierarchy of tier-1 suppliers. Likewise, various papers propose lists of selection criteria (e.g., environmental, social, and economic), especially in supplier selection based on literature review alone, but few apply a formal, consensus-driven screening and weighting process. In contrast, our study (1) uses Fuzzy Delphi to systematically refine criteria under uncertainty for sustainable tier-1 supplier selection, (2) employs SWARA and Borda to obtain numeric and ordinal consensus weights without additional expert rounds, and (3) applies these weights to rank tier-1 suppliers; thus offering the first comprehensive, uncertainty-aware, and bias-mitigated approach to sustainable supplier tiering.

Major contributions of this study are summarized as follows:

1. Introducing a novel framework comprising fuzzy Delphi, Borda, and SWARA approaches to identify the importance of criteria in the sustainable tier-1 supplier selection process. The fuzzy Delphi stage narrows the criteria with fuzzy evaluations and systematically converts and aggregates linguistic expert judgments into fuzzy numbers, ensuring that only sustainability criteria are adopted.
2. Employing SWARA-Borda approaches to determine the significance of the criteria. We apply SWARA's stepwise numeric comparisons to minimize expert load, then improve ranking accuracy and minimize outlier influence by inputting the initial SWARA weights into the Borda method, eliminating the need for additional data gathering.
3. Conducting head-to-head comparisons of SWARA, SWARA+Borda, Analytic Hierarchy Process (AHP), and Best–Worst Method (BWM)-reporting Spearman correlations, and concrete rank shifts to demonstrate the robustness and added value of our hybrid weighting approach.
4. Illustrating a step-by-step workflow and its adaptation in an Iranian spare parts supplier, to other industries, demonstrating that the Fuzzy Delphi-Borda-SWARA model can provide reliable weights.

5. Developing a comprehensive and dependable list of effective criteria for selecting sustainable tier-1 suppliers is compiled, bringing together information from various sources.
6. Utilizing MADM methods to identify the most crucial and superior criteria for sustainable tier-1 suppliers, mitigating confusion for companies in selecting the most influential parameters for determining tier-1 suppliers.

The remainder of the manuscript is organized as follows. Section 2 reviews the most relevant studies conducted in the literature. Section 3 presents the developed methodology in detail. The main findings and results are represented in Sect. 4, and then discussed in Sect. 5. Finally, Sect. 6 concludes the study and provides useful future research directions.

2 Literature survey

Initially, simulation studies such as beer games were conducted to investigate supply chain dynamics, highlighting the significant influence of suppliers' decisions on production target delays and meeting customer demands. Nevertheless, emphasis was primarily placed on suggesting effective coordination mechanisms between an OEM and its major suppliers (i.e., tier-1). However, with the widespread adoption of tiering concepts, it is now recognized that strategies and decision-making processes must be synchronized at a higher level than tier-1 suppliers, including lower-tier suppliers and particularly tier-2 suppliers (Mena, 2013). Therefore, the literature on this subject can be explored from two vantage points: (i) selecting and tiering of suppliers and (ii) criteria for tier-1 supplier selection.

2.1 Supplier selection and tiering

There are also lots of studies addressing sustainable supplier selection in different supply chains, which highlights the significance of the selection of suppliers and their tiering (Lin & Lin, 2024). Of course, before emerging as a subject of academic inquiry, the challenges inherent in OEM-supplier relationships and suppliers across different tiers were recognized as practical challenges in Supply Chain Management (SCM). This recognition has prompted a wide range of studies by management science, organizational psychology, and industrial engineering experts. However, the complexity of these challenges is further accentuated by contemporary market dynamics, including concepts such as lean practices, agility, and flexibility. Consequently, diverse strategies have been introduced to foster the development and orchestration of deeper relationships within the supply chain, particularly between OEMs and their primary suppliers, aimed at their effective management.

Awasthi et al. (2018) proposed a fuzzy AHP-VIekriterijumsko KOMPromisno Rangiranje (VIKOR) framework for sustainable global supplier selection, considering risks from sub-suppliers. Economic criteria weighed the most, highlighting a need for increased emphasis on global risk. This framework offered a managerial tool to effectively manage sustainability risks in complex supply chains. Manello and Calabrese (2019) conducted an ex-post analysis on tier-1 supplier selection in the automotive industry using an original database and web-sourced information. Their study emphasized the pivotal role of reputation over traditional criteria. Diversified customer portfolios and exposure to premium brands

enhanced supplier attractiveness. The cross-case study by Lechler et al. (2020) investigated stakeholder influences, identifying factors impacting tier-1 suppliers' sustainability efforts and providing valuable insights for decision-makers. Cui et al. (2023) proposed a hybrid model that addresses gaps in theoretical studies, integrating fuzzy set theory and Bayesian networks for effective, sustainable supplier selection across multi-tier supply chain structures. In the contemporary focus on sustainable corporate practices, scant empirical knowledge exists on why tier-1 suppliers integrate sustainability into their selection processes.

Bošković et al. (2023) suggested an integrated model based on Criteria Importance Assessment (CIMAS) and CRiteria Importance Through Intercriteria Correlation (CRITIC) methods for assessing criteria importance in supplier selection. The approach identified on-time distribution as the top criterion, incorporating expert experience and objective data.

When examining studies on sustainable supplier selection that incorporate well-known Multi-Criteria Decision-Making (MCDM) approaches, particularly those published after 2020, several key papers are highlighted here. Tavana et al. (2021) introduced a fuzzy green supplier selection model aimed at enhancing sustainability in supply chains within the context of reverse logistics. A novel hierarchical fuzzy BWM was employed to find the importance weights of green criteria and sub-criteria. Hybrid models, including fuzzy extensions of Complex Proportional Assessment (COPRAS), Multi-objective Optimisation by Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA), and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) were then used to evaluate and rank suppliers according to their recycling capabilities. Yazdani et al. (2022) proposed a two-phase sustainable multi-tier supplier selection model for food supply chains. They ranked various tier suppliers using the Measurement of Alternatives and Ranking according to the COmpromise Solution (MARCOS)-D approach and employed SWARA and Level Based Weight Assessment (LBWA) to estimate supplier selection criteria weights. Boz et al. (2022) examined the impact of COVID-19 on sustainable supplier selection. The fuzzy BWM method was utilized for determining criterion weights, while the fuzzy Additive Ratio Assessment (ARAS) method was applied for supplier selection. Koc et al. (2023) presented a novel approach to sustainable supplier selection by incorporating economic, social, and environmental sustainability dimensions, alongside innovation, lean principles, and knowledge management. A novel Monte Carlo-based MCDM model was developed to address probabilistic uncertainty. The Monte Carlo simulation was integrated with the AHP and TOPSIS to determine criteria weights and conduct supplier evaluations, respectively. Singh et al. (2025) examined sustainable supplier selection within a construction firm through a novel MCDM method based on dominance-based rough set theory and implemented using the 'jrank' software tool. Sithi et al. (2025) evaluated sustainability practices in the Bangladeshi textile industry and identified criteria for sustainable supplier selection through a literature review, expert opinions, and SWARA and TOPSIS methods, utilizing real-world supplier data for validation.

This study clearly distinguished between (a) the many studies that propose fixed sets of sustainability criteria based solely on literature survey or company requirements (e.g., Afrasiabi et al., 2022; García et al., 2022; Kusi-Sarpong et al., 2023; Shang et al., 2022; Yazdani et al., 2021) and (b) the far fewer works that systematically derive and validate those criteria via expert consensus under uncertainty (e.g., Delphi and fuzzy Delphi proposed by Gidi-agba et al., (2023) and Torres Vergara et al. (2024), respectively).

2.2 Selection criteria for tier-1 suppliers

Upon the foregoing discussion, tiering emerges as an imperative undertaking essential for contemporary manufacturing industries seeking to expand operations, curtail costs, and enhance supplier management. However, pivotal questions persist regarding classifying suppliers into tier-1 status and the defining characteristics they should embody.

Despite numerous research endeavors, a definitive consensus on the attributes of tier-1 suppliers remains elusive, with studies sporadically proposing various characteristics. For example, Kazançoğlu et al. (2023) introduced a multi-stage framework with 14 criteria, emphasizing environmental factors in the food industry throughout multi-tier supply chains. Though they propose a multi-stage framework with extensive sustainability criteria, no prior work systematically combines uncertainty-driven criterion screening, lightweight numeric elicitation, and ordinal consensus aggregation in a single end-to-end process for tier-1 supplier selection. However, when selecting the tier-1 supplier, these criteria did not seem complete and comprehensive. Consequently, through an exhaustive literature review, we compiled an extensive list of 35 criteria, synthesized from the relevant references shown in Table 1.

2.3 Overview of key contributions

The most relevant work is Kazançoğlu et al. (2023), which outlines the criteria for implementing sustainability standards in a multi-tier sustainable supply chain and ranking suppliers and how these criteria should be prioritised among different tiers with BWM and Preference Ranking Organization METHod for Enriched Evaluation (PROMETHEE) methods. Our study differs by adding a Borda count stage, using the SWARA outputs as “votes”, to preserve ordinal consensus and mitigate numeric outlier bias without further expert input. Furthermore, we only focused on the tier-1 suppliers to reveal the importance level of the criteria, not the ranking of suppliers. This approach allows us to gain deeper insights into the significance of each criterion in relation to sustainability, particularly in the context of tier-1 suppliers. Therefore, the main contributions are summarized as follows:

1. *Full Uncertainty-to-Ordinal Pipeline* Unlike prior hybrid approaches, we begin with fuzzy Delphi screening, proceed with SWARA’s stepwise numeric comparisons, and then apply Borda count directly to the SWARA weights, achieving both magnitude and rank-order consensus in one workflow.
2. *No Additional Expert Rounds* We reuse the initial SWARA assessments as Borda inputs, streamlining data collection and preserving expert effort.
3. *Comparative Validation* We conduct head-to-head comparisons among SWARA, SWARA+Borda, AHP, and BWM-reporting Spearman ρ values and rank shifts to empirically demonstrate our method’s robustness and added value.
4. *Clustering Analysis for Deeper Insight* We apply Principal Component Analysis (PCA) followed by K-Means clustering to group the finalized criteria based on expert rankings, revealing hidden patterns among the decision factors and enriching the interpretability and analytical depth of the selection framework.

3 Research methodology

Several studies have applied Delphi (Gupta & Shaikh, 2024), fuzzy-Delphi (Torres Vergara et al., 2024), SWARA (Sithi et al., 2025), Hesitant SWARA (Rani et al., 2020) in sustainable supplier selection and Borda (Ristono, 2025) in supplier ranking without obtaining criteria weights individually or any pairwise combinations (Fuzzy Delphi-Borda-SWARA). However, none integrates all three components; i.e., fuzzy-Delphi, SWARA, and Borda, into a unified pipeline. As outlined, this study aims to delineate and rank selection criteria pertinent to tier-1 suppliers. The research methodology, depicted in Fig. 3, involves several sequential steps. Initially, an extensive inventory of criteria for tier-1 suppliers, as documented in the research literature, is compiled. Subsequently, employing the Fuzzy Delphi method, these identified criteria undergo prioritization and arrangement. Following this, a refined subset of criteria is determined by applying the Borda method. Lastly, expert opinions are leveraged within the SWARA method to assign weights to the selected criteria.

Expert assessments of criterion relevance are often expressed in linguistic terms (e.g., “high,” “medium,” “low”) and are subject to individual interpretation. Fuzzy Delphi converts these linguistic judgments into fuzzy numbers and aggregates them, thus preserving the vagueness inherent in expert opinions while eliminating outliers through consensus thresholds. Traditional approaches, like the Nominal Group Technique, AHP, and BWM, require crisp numerical comparisons from the outset, which can force premature precision and amplify individual biases. Our Fuzzy Delphi stage screens and refines the criterion set under uncertainty before any numeric weighting, ensuring that only well-supported criteria proceed to weighting.

SWARA requires experts to compare each criterion only against the one immediately above it in the ranking, reducing the total number of comparisons from $n(n-1)/2$ (AHP) or $2n-3$ (BWM) to $n-1$. This stepwise process reduces cognitive fatigue and accelerates data gathering while maintaining transparency.

Even after fuzzy screening, experts may diverge in the fine-grained numeric weights they assign. Borda’s rank-based point system captures the full ordering of each expert’s preferences, counteracting situations where a minority’s extreme score might distort a simple average. By integrating Borda, we explicitly preserve ordinal consensus and guard against numeric outliers. We selected methods according to three key requirements for sustainable tier-1 supplier criteria:

1. *Uncertainty-Handling* Experts express criterion importance in linguistic terms under ambiguity. Fuzzy Delphi uniquely transforms and aggregates these into consensus fuzzy scores, whereas alternatives like crisp Delphi or simple literature surveys cannot capture vagueness.
2. *Cognitive Load Minimization* With potentially dozens of criteria, methods requiring extensive pairwise judgments (e.g., AHP’s $n(n-1)/2$ comparisons) risk expert fatigue. SWARA reduces the burden to $n-1$ stepwise comparisons, balancing efficiency and transparency.
3. *Bias Mitigation and Ordinal Consensus* Simple averaging of numeric weights can mask rank disagreements; Borda count preserves each expert’s full ranking without soliciting new data. While BWM also reduces comparisons and offers consistency checks, it

Table 1 Summary of the expert views on selection criteria for the tier-1 suppliers

No	Descriptions	Cox (1996)	Taherdoost and Beard (2019)	Cusumano & Takeishi (1991)	Volpato (2004)	Lambert et al. (1998)	Giddiga et al. (2023)	Durmic (2019)	Levy (2010)	Kane & Trimble (2008)	Roy et al. (2020)	Frigant and Lung (2002)	Dammenberg & Kleinhaus (2004)	Grimm et al. (2014)	Viswanadham and Samvedi (2013)	Gold and Awasthi (2015)	Najafi NObar and Setak (2010)	Manucharyan (2021)	Sheykhtzadeh et al. (2024)
1	Large-scale business	*																	
2	Proper manufacturing and supply capabilities	*										*							
3	Practical knowledge of manufacturing processes		*																
4	Developing a design process		*																
5	Ability in product engineering		*																
6	Ability to harness collaboration for new product development		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
7	Management links with OEM				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
8	Performing product R&D activities				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
9	Ability to develop products and manufacturing processes				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
10	Providing services to many OEMs				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
11	Capacity to establish supply networks in the downstream				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
12	Influence on keeping a competitive price		*		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
13	Acceptable financial capability				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
14	High management abilities				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
15	Ability to produce modules				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
16	Joint investment for module development				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
17	Engineering services				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
18	Final product assembly				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
19	Trust between the tier-1 supplier and OEM		*		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
20	Taking risks transferred from an OEM				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
21	Collaborate with other tiers				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
22	Price volatility adaptability				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*

Table 1 (continued)

No	Descriptions	Cox (1996)	Taherdoost (2019)	Cusumano & Takeishi (1991)	Volpato (2004)	Lambert et al. (1998)	Gidigha et al. (2023)	Durmic (2019)	Levy (2010)	Kane & Trimble (2008)	Roy et al. (2020)	Frigant Lung (2002)	Dammenberg & Kleinhans (2004)	Grimm et al. (2014)	Viswanadham and Samvedi (2013)	Gold and Awashti (2015)	Najafi NObar and Setak (2010)	Manucharyan (2021)	Sheykhdah et al. (2024)		
23	Having proper infrastructure													*							
24	Compatibility with global policies														*						
25	Compatibility in the global economy														*						
26	Higher flexibility															*					
27	Acceptable reaction (speed)															*					
28	Acceptable innovations															*					
29	Environmental concerns	*					*				*					*					*
30	Social indicators															*					*
31	Good quality of products	*					*				*					*					*
32	Proper product pricing															*					*
33	Highly experienced & good reputation (Credit)	*					*				*					*					*
34	Enabling guarantees in produced components																*				*
35	Component/product Delivery time	*					*				*					*					*

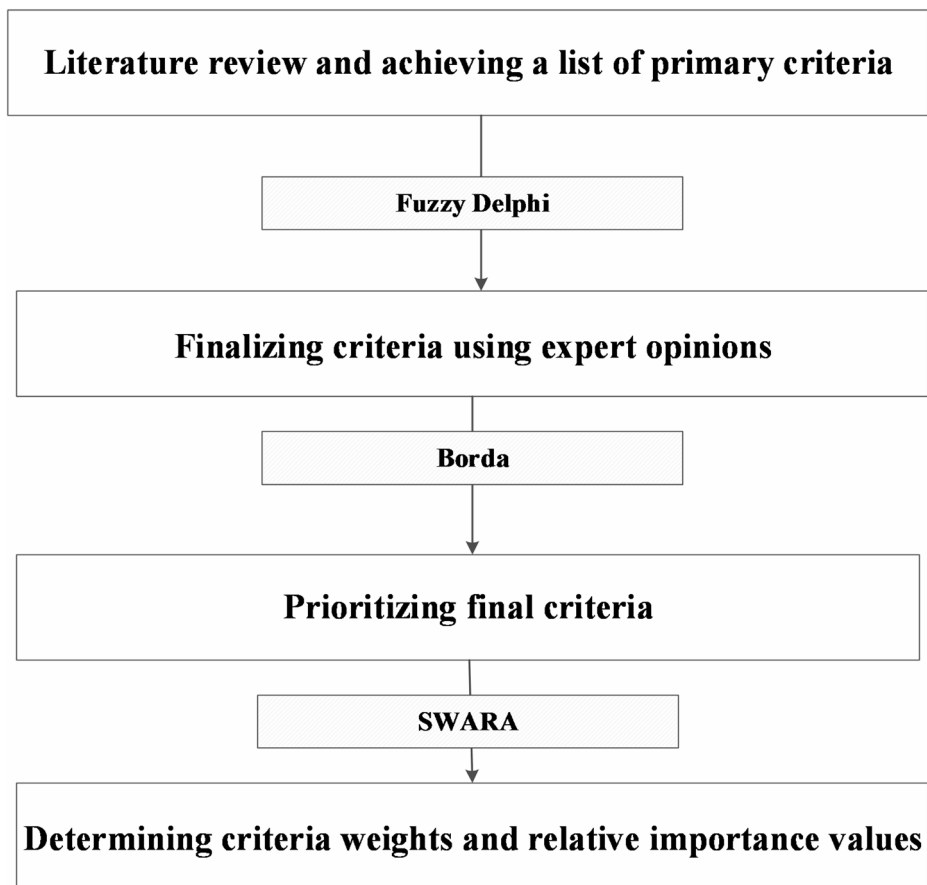


Fig. 3 Flowchart of the research methodology

focuses solely on best/worst distinctions and does not preserve the complete ordinal sequence.

We recognized that other MCDM techniques (e.g., Decision-Making Trial and Evaluation Laboratory (DEMATEL), ELimination Et Choix Traduisant la REalité (ELECTRE), AHP, and BWM) could also be applied for screening or weighting; however, these techniques often either do not accommodate fuzzy-Delphi's uncertainty handling or require more complex computations and data elicitation. Although other hybrid approaches are available, each has limitations, such as requiring excessive comparisons, missing ordinal consistency measures, or being unable to effectively capture linguistic ambiguity. The proposed Fuzzy Delphi-Borda-SWARA model was therefore chosen as the most coherent means to achieve uncertainty-aware screening, efficient numeric elicitation, and bias-resilient aggregation in a single, streamlined process.

3.1 Delphi method

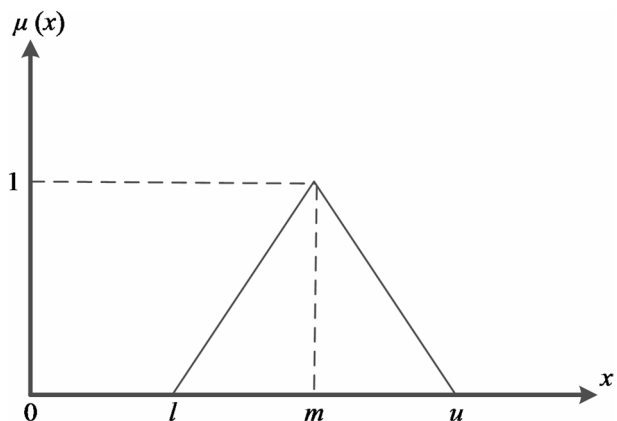
The Delphi technique constitutes a systematic approach for soliciting and aggregating informed assessments from a panel of experts regarding a specific subject matter. It serves both as a research methodology and a data collection strategy. According to Enzer (1971), the Delphi method typically outperforms alternative approaches for extracting and processing judgments due to its focused nature, which provides a structured framework for individuals from diverse backgrounds and positions to collectively address a given problem. Moreover, this method reduces administrative burdens and documentation costs.

Nevertheless, the Delphi method remains an evolving technique, with its effectiveness likely correlated with its relative simplicity in implementation. Although this process does not require advanced mathematical skills or high-level analytical abilities, it does call for strong project design expertise, a thorough understanding of the relevant issues, and competence in using the Delphi technique. Fuzzy Delphi is employed to refine the final expert-approved list, while Borda method is integrated into SWARA for ranking criteria before the weight assignment. In practice, the preliminary prioritization of criteria, constituting the initial phase of SWARA, is conducted using the Borda method. SWARA comprises the computation of the definitive weight assigned to each criterion, which may be incorporated in the ranking procedure or the selection of tier-1 suppliers based on indicator weights.

3.2 Fuzzy sets

Fuzzy logic, initially introduced by Zadeh (1965), addresses the inherent uncertainty prevalent in real-world decision-making scenarios, where objectives, constraints, and measures often remain elusive. Rather than attempting to integrate diverse experiences, opinions, ideas, and motivations from individual or group decision-makers, fuzzy logic translates the linguistic expressions into fuzzy numbers to enable evaluative judgments (Gokulachandran et al., 2025). Triangular fuzzy numbers denoted as $\tilde{A} = (l, m, u)$, feature lower (l), middle (m), and upper (u) limits representing the fuzzy set, satisfying the condition ($l \leq m \leq u$). The membership function for triangular fuzzy numbers is delineated in Eq. (1). Figure 4 illustrates a schematic depiction of fuzzy numbers (Akyuz & Celik, 2015). Two triangular

Fig. 4 Triangular fuzzy numbers (Akyuz & Celik, 2015)



fuzzy numbers denoted as $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$, entail specific mathematical computations.

$$\mu_{\tilde{A}} = \begin{cases} 0, & \text{if } x < l, \\ \frac{(x-l)}{(m-l)}, & \text{if } l \leq x \leq m, \\ \frac{(u-x)}{(u-m)}, & \text{if } m \leq x \leq u, \\ 0, & \text{if } x \geq u. \end{cases} \quad (1)$$

In the literature, different fuzzy systems have been utilized by researchers to develop a variety of solution methods in the field of decision-making, such as fuzzy hypersoft sets (Bansal et al., 2022; Dhumras & Bajaj, 2023a, b) and picture fuzzy sets (Dhumras & Bajaj, 2024; Dhumras et al., 2023). Here, the fuzzy Delphi method is employed as one of the well-known techniques to prioritize criteria for selecting the primary supplier.

3.3 Fuzzy Delphi method

The traditional "Project DELPHI," initially conducted by Dalkey and Helmer (1963) at the RAND Corporation (Dalky & Helmer, 1963), evolved into a widely adopted management practice. Delphi methodology hinges on three key characteristics aimed at gauging the consensus level within an expert panel: anonymity, repetition, controlled feedback, and statistical summaries of panel responses.

However, the conventional Delphi method may encounter challenges such as lower convergence of opinions, heightened operational costs, and the potential exclusion of critical ideas by organizers. In response, Murry et al. (1985) proposed a hybrid approach by combining the traditional Delphi method with fuzzy set theory to mitigate ambiguity and requirement inconsistencies. Triangular fuzzy numbers are employed to capture expert opinions, giving rise to the fuzzy Delphi technique. In this technique, the maximum and minimum values derived from expert opinions serve as the endpoints of triangular fuzzy numbers, while the geometric mean serves as the membership degree within these numbers, thereby circumventing extreme values. Unlike the traditional Delphi method, which typically requires multiple survey rounds to achieve consensus, the fuzzy Delphi technique necessitates only a single survey round encompassing all expert views.

In evaluating the significance of performance measurement attributes, while the traditional Delphi method employs a 10-point scale, this study adopts a 5-point scale due to practical complexities. The fuzzy Delphi method utilizes the geometric mean as a foundational metric for aggregating group decisions, thereby screening out inappropriate factors and mitigating extreme values. This approach not only reduces costs and time but also empowers decision-makers to quantify the fuzziness inherent in decision data and processes, ultimately leading to more optimal selections (Chang, 1998). The subsequent step involves determining the fuzzy trigonometric function of each critical factor based on experts' responses to a questionnaire, following Eqs. (2)–(3):

$$\tilde{A} = (L_A, M_A, U_A), \quad (2)$$

$$L_A = \min(X_{A_i}) \quad (i = 1, 2, \dots, n), \quad (3)$$

$$M_A = (X_{A_1} \times X_{A_2} \times \cdots \times X_{A_n})^{\frac{1}{n}}, \quad (4)$$

$$U_A = \max(X_{A_i}) \quad (i = 1, 2, \dots, n), \quad (5)$$

where \tilde{A} denotes the assessment value of the critical factor A ; with L_A , M_A , and U_A denoting the lower bound, geometric mean, and upper bound values for factor A , respectively. Moreover, X_{A_i} represents the value assigned by the i^{th} decision-maker for factor A .

However, the fourth step entails defining SA as the measure reflecting consensus in group decision-making regarding this factor.

$$SA = (U_A + 4 \times M_A + L_A) / 6. \quad (6)$$

In the fifth step, the threshold value S is selected to filter out inappropriate factors. In this case,

$$\text{if } SA \geq S, \text{ then the critical factor } A \text{ is accepted,} \quad (7)$$

$$\text{if } SA < S, \text{ then critical factor } A \text{ is deleted.} \quad (8)$$

3.4 SWARA method

In many MADM scenarios, weighting alternatives stands as one of the key procedures in problem-solving (Zolfani et al., 2013). In such cases, the involvement of experts in evaluating and assigning weights to alternatives constitutes an integral aspect of the decision-making process. The SWARA method, introduced by Kresolin et al. (2010), facilitates decision-makers in the selection, evaluation, and weighting of alternatives. A significant advantage of this approach lies in its capability to assess the accuracy of expert opinions regarding the allocation of weights to attributes (Keršulienė et al., 2010). Moreover, expert consultations have been shown to yield more precise results compared to other common MADM methodologies (Dehnavi et al., 2015). Figure 5 depicts the weighting process utilizing the SWARA method (Keršulienė & Turskis, 2011).

If there are n alternatives, the primary steps involved in determining criteria weights using the SWARA method are outlined below:

Step 1: Ranking Final Criteria

Initially, the metrics identified by decision-makers are designated as the final criteria, after which all attributes are ranked in order of significance. Consequently, the most and least important attributes occupy the highest and lowest-ranking positions, respectively.

Step 2: Determining the Relative Importance of S_j

Now, the relative importance of each criterion is measured for the most important precedent. This value is represented by S_j .

Step 3: Determining Values of Coefficient K_j

The coefficient K_j , as a function of the relative importance of each criterion, is determined by Eq. (7):

$$K_j = S_j + 1 \quad (j = 1, 2, \dots, n). \quad (9)$$

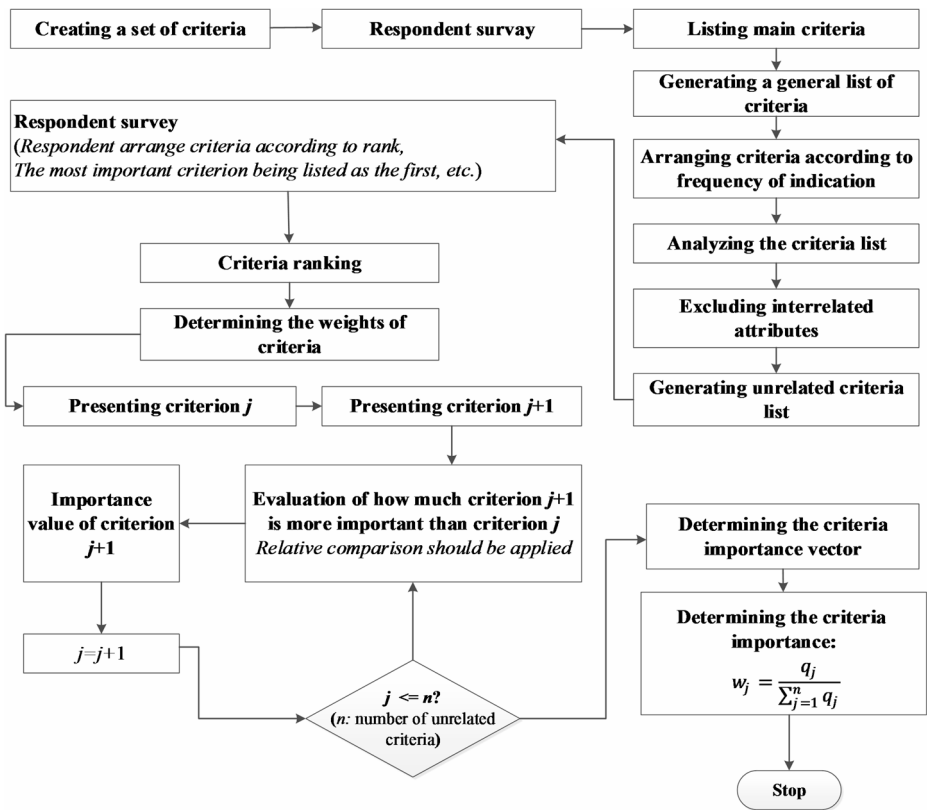


Fig. 5 Flowchart of the weighting steps in SWARA (Keršulienė & Turskis, 2011)

Step 4: Calculating Initial Weights for Criteria.

The initial weight of each criterion is calculated by Eq. (8). Here, the weight of the first attribute, i.e., the most important one is generally considered equal to 1.

$$q_j = \frac{q_{j-1}}{K_j} \quad (j = 1, 2, \dots, n). \tag{10}$$

Step 5: Calculating Final Normalized Weights.

In the concluding stage of the SWARA procedure, the final weights, known as normalized weights, are computed using Eq. (9):

$$w_j = \frac{q_j}{\sum q_j} \quad (j = 1, 2, \dots, n). \tag{11}$$

As previously mentioned, the SWARA method constitutes a prevalent weighting technique employed by various scholars. Notably, Kresolin et al. (2010) applied SWARA to reach a consensus in resolving disputes, while Alimardani et al. (2013) utilized it in supplier selection dilemmas. Additionally, Sarfaraz et al. (2013) employed the SWARA method in prod-

uct design, and Hashemkhani et al. (2014) utilized it to prioritize investment alternatives within the high-technology industry. More detailed information about the Borda method can be found in Boyaci (2021) and Lamboray (2007).

3.5 Borda method

The Borda method is a well-known practical approach for establishing consensus among decision-makers in ranking options. In this method, each option ranked by the decision-makers is assigned a score. These scores are then combined in specific ways, ultimately ordering the options in descending rank. The Borda method is a preference-based voting system where voters prioritize options by ranking them. Then, by summing the scores for each option, a weighted priority is established. Barak and Mokfi (2019) outline the following steps to implement the Borda method:

Step 1. Each voter ranks the options,

Step 2. Contrary to the ranking order, each voter assigns higher scores to the lower-ranked options (various scoring methods exist),

Step 3. The scores assigned to each option by voters are summed,

Step 4. Based on the scores from Step III, the options are ranked.

For further details on this method, see Xiao et al. (2017) and Zavadskas et al. (2017).

As described in the steps of the SWARA method, the first step requires experts to rank the criteria. Since there is no specific methodology provided for this ranking, the aim is to address this challenge by utilizing the Borda method. To this end, after training the experts on the Borda method, we asked them, with support from their subordinate specialists, to rank the criteria identified through the fuzzy Delphi method. Next, the weights of the criteria were calculated using the steps of the SWARA method.

Additionally, to conduct a sensitivity analysis and evaluate the findings from the SWARA method, we performed a second round of criteria ranking using the Borda method and then compared these results with the final rankings obtained from the SWARA method.

4 Results

Based on the procedures described here, this section presents and discusses the research results.

4.1 List of final assessment attributes

Following the research procedures, a set of 35 criteria was initially defined for selecting sustainable tier-1 suppliers through a literature review. However, to refine and contextualize the initial assessment criteria, a fuzzy Delphi questionnaire was administered to a panel of six experts. Given the limited research studies in this field and its early stage of development, panel members were selected based on their expertise and research backgrounds. Two panelists are faculty members with extensive research experience in this domain, while the remaining members hold graduate degrees and managerial positions in the automotive industry.

Most MCDM studies commonly employ panels of 5–10 experts to balance diversity of perspectives with manageability of data collection and analysis (e.g., Cui et al., 2023; Tavana et al., 2021). A panel of six experts falls squarely within this recommended range and has been shown to yield reliable consensus in sustainability and supplier-selection contexts. Four experts are senior practitioners (E2, E3, E4, and E5) directly responsible for supplier evaluation in manufacturing contexts, and two are academic researchers (E1 and E6) with extensive publication records in MCDM and fuzzy sets. Together, they cover procurement strategy, quality assurance, environmental compliance, and methodological rigor in decision-support systems, ensuring that criterion screening and weighting reflect both practical and theoretical considerations. These additions clarify why a six-expert panel is appropriate, demonstrate the experts' qualifications, and provide empirical evidence of the results' stability. We trust this addresses the reviewer's concern regarding generalizability and expert selection. Table 2 outlines each expert's domain expertise, organizational role, and years of experience:

To design the questionnaire, parameters from Table 1 of reputable publications served as the foundation, supplemented by an open-ended question prompting participants to suggest additional essential factors for consideration. Subsequently, the questionnaire was distributed among the expert panel to solicit their opinions and determine the relative importance and priority values of the factors. The experts assessed each factor on a 5-point scale, assigning scores between 1 and 5.

It is important to acknowledge that determining the threshold value for selecting critical factors via the fuzzy Delphi method involves subjective inference, directly influencing the number of factors retained. Despite lacking a definitive rule, expert opinions guided the establishment of a threshold value, denoted as S , set to 4.5. Consequently, factors with a score below 4.5 were eliminated. Table 3 provides a summary of expert inputs and the decision-making process for each factor. With the threshold value set at 4.5, the number of final criteria for sustainable tier-1 supplier selection was reduced to 10, as depicted with bold numbers in Table 3.

4.2 Criteria weighting & prioritization

Once the assessment attributes were finalized, a panel of experts was assembled according to the research procedures. This panel was comprised of four practitioners from one of the

Table 2 Expert's domain expertise, role, and years of experience

Expert ID	Role	Years of experience	Relevant expertise
E1	Assistante professor, industrial engineering	20	Decision-support systems
E2	Strategic sourcing specialist	25	Risk assessment, procurement analytics
E3	Supply chain director	21	Logistics, sustainability metrics
E4	Senior quality assurance manager	19	Supplier auditing, environmental compliance
E5	Chief procurement officer	23	Tier-1 supplier evaluation, green sourcing
E6	Professor, supply chain management	24	MCDM methods, fuzzy systems

Table 3 Summary of the fuzzy Delphti questionnaire

No	Criteria	E1	E2	E3	E4	E5	E6	U _A	L _A	M _A	SA	Status
1	Large-scale business	4	4	5	5	5	2	5	2	3.984	3.823	Eliminated
2	Proper manufacturing and supply capabilities	5	5	5	4	5	4	5	4	4.642	4.594	Retained
3	Practical knowledge of manufacturing processes	4	5	5	5	4	5	5	4	4.642	4.594	Retained
4	Developing a design process	3	5	5	4	5	5	5	3	4.424	4.283	Eliminated
5	Ability in product engineering	3	5	5	5	5	4	5	3	4.424	4.283	Eliminated
6	Ability to harness collaboration for new product development	4	5	5	5	5	5	5	4	4.817	4.712	Retained
7	Management links with OEM	3	4	4	5	4	3	5	3	3.772	3.848	Eliminated
8	Performing product R&D activities	4	5	5	3	5	4	5	3	4.263	4.175	Eliminated
9	Ability to develop products and manufacturing processes	4	5	5	4	4	5	5	4	4.472	4.481	Eliminated
10	Providing services to many OEMs	4	5	4	5	5	4	5	4	4.472	4.481	Eliminated
11	Capacity to establish supply networks in the downstream	4	5	5	5	5	5	5	4	4.817	4.712	Retained
12	Influence on keeping a competitive price	5	5	5	4	4	4	5	4	4.472	4.481	Eliminated
13	Acceptable financial capability	5	5	5	5	4	3	5	3	4.424	4.283	Eliminated
14	High management abilities	4	5	5	4	5	4	5	4	4.472	4.481	Eliminated
15	Ability to produce modules	5	5	5	5	4	4	5	4	4.642	4.594	Retained
16	Joint investment for module development	5	5	5	5	4	2	5	2	4.135	3.923	Eliminated
17	Engineering services	4	5	5	4	4	4	5	4	4.309	4.373	Eliminated
18	Final product assembly	2	5	5	3	5	1	5	1	3.014	3.009	Eliminated
19	Trust between the tier-1 supplier and OEM	4	5	5	5	5	4	5	4	4.642	4.594	Retained
20	Taking risks transferred from an OEM	5	5	5	5	4	3	5	3	4.424	4.283	Eliminated
21	Collaborate with other tiers	4	5	5	5	5	2	5	2	4.135	3.923	Eliminated
22	Price volatility adaptability	5	5	5	4	5	3	5	3	4.424	4.283	Eliminated
23	Having proper infrastructure	4	5	5	5	5	4	5	4	4.642	4.594	Retained
24	Compatibility with global policies	4	5	5	3	3	3	5	3	3.732	3.821	Eliminated
25	Compatibility in the global economy	3	5	4	4	3	3	5	3	3.595	3.730	Eliminated
26	Higher flexibility	4	5	5	4	4	4	5	4	4.309	4.373	Eliminated
27	Acceptable reaction (speed)	5	5	5	4	5	4	5	4	4.642	4.594	Retained
28	Acceptable innovations	5	5	5	5	5	4	5	4	4.817	4.712	Retained

Table 3 (continued)

No	Criteria	E1	E2	E3	E4	E5	E6	U _A	L _A	M _A	SA	Status
29	Environmental concerns	5	5	5	5	4	1	5	1	3.684	3.456	Eliminated
30	Social indicators	3	5	4	3	3	1	5	1	2.854	2.902	Eliminated
31	Good quality of products	3	5	5	5	5	4	5	3	4.424	4.283	Eliminated
32	Proper product pricing	5	5	5	4	4	4	5	4	4.472	4.481	Eliminated
33	Highly experienced & good reputation (Credit)	4	5	5	4	4	3	5	3	4.107	4.071	Eliminated
34	Enabling guarantees in produced components	5	5	5	4	5	5	5	4	4.817	4.712	Retained
35	Component/product Delivery time	4	4	5	5	5	4	5	4	4.472	4.481	Eliminated

country's largest automotive part manufacturing companies and two academic professors specializing in this field.

Initially, experts were tasked with prioritizing selected criteria using Table 3 and the Borda method. This process rendered a list of 10 significant criteria for sustainable tier-1 supplier selection:

1. Proper manufacturing and supply capabilities (A),
2. Practical knowledge of manufacturing processes (B),
3. Ability to harness collaboration for new product development (C),
4. Capacity to establish supply networks in the downstream (D),
5. Ability to produce modules (E),
6. Trust between the tier-1 supplier and OEM (F),
7. Having proper infrastructure (G),
8. Acceptable reaction (speed) (H),
9. Acceptable level of innovation (I),
10. Enabling guarantees for produced components (J).

Subsequently, the SWARA method was employed to weigh and prioritize these criteria. Following Step 1 and utilizing the output of the Borda method, the criteria were ranked in descending order of importance. The outcomes of Steps 2, 3, and 4 were depicted in the third, fourth, and fifth columns of Table 4, respectively. Finally, in the concluding step of the SWARA method, along with the weight normalization process, the expert panel computed the final weights for the selected criteria. Table 4 presents the results of this process for tier-1 supplier selection based on E1.

The final results of the criteria weighting by the remaining experts (E2-E6) are presented in Table 5.

To aggregate the weights provided by the experts, the Geometric Mean Method (GMM) was employed (Forman & Peniwati, 1998). Consequently, the final weight of critical criteria for tier-1 supplier selection was calculated using the geometric mean. However, to normalize the weighted aggregate of each criterion, this value was divided by the total aggregated weights for all criteria. The resulting values are presented in the final column of Table 6.

Figure 6 presents a comparative analysis of weighted criteria for the tier-1 supplier selection process from the perspectives of different experts. In the final stage of selecting tier-1

Table 4 Calculations of the criteria weights for tier-1 supplier selection by E1

Criteria	Comparative importance of average value (S_j)	Coefficient ($K_j = S_j + 1$)	Recalculated weight ($q_j = \frac{q_{j-1}}{K_j}$)	Weight ($W_j = \frac{q_j}{\sum q_j}$)
A	1	1	1	0.1455
C	0.03	1.03	0.971	0.1412
B	0.2	1.2	0.809	0.1177
G	0.01	1.01	0.801	0.1165
E	0.06	1.06	0.756	0.1099
D	0.15	1.15	0.657	0.0956
J	0.03	1.03	0.638	0.0928
H	0.17	1.17	0.545	0.0793
F	0.36	1.36	0.401	0.0583
I	0.35	1.35	0.297	0.0432

Table 5 Calculations of the criteria weights for tier-1 supplier selection by E2–E6

E2	E3					E4					E5					E6									
	Criterion	S_j	K_j	q_j	W_j	Crit-	S_j	K_j	q_j	W_j	Crit-	S_j	K_j	q_j	W_j	Crit-	S_j	K_j	q_j	W_j	Crit-	S_j	K_j	q_j	W_j
						te-					te-					te-					te-				
						rion					rion					rion					rion				
A	1	1	1	1	0.2483	A	1	1	1	0.1680	A	1	1	1	0.1875	C	1	1	1	0.1721	E	1	1	1	0.1961
C	0.36	1.36	0.735	0.1826	D	0.11	1.11	0.901	0.1514	B	0.05	1.05	0.952	0.1785	D	0.09	1.09	0.917	0.1579	D	0.04	1.04	0.962	0.1886	
D	0.26	1.26	0.584	0.1449	E	0.05	1.05	0.858	0.1442	D	0.13	1.13	0.843	0.1580	I	0.2	1.2	0.765	0.1316	B	0.19	1.19	0.808	0.1585	
E	0.52	1.52	0.384	0.0953	C	0.31	1.31	0.655	0.1101	E	0.39	1.39	0.606	0.1137	B	0.02	1.02	0.750	0.1290	F	0.38	1.38	0.586	0.1148	
B	0.16	1.16	0.331	0.0822	F	0.01	1.01	0.648	0.1090	C	0.29	1.29	0.470	0.0881	A	0.24	1.24	0.604	0.1040	A	0.18	1.18	0.496	0.0973	
G	0.16	1.16	0.285	0.0708	I	0.39	1.39	0.467	0.0784	F	0.27	1.27	0.370	0.0694	G	0.37	1.37	0.441	0.0759	H	0.1	1.1	0.451	0.0885	
H	0.06	1.06	0.269	0.0668	H	0.02	1.02	0.457	0.0769	I	0.05	1.05	0.352	0.0661	E	0.01	1.01	0.437	0.0752	G	0.4	1.4	0.322	0.0632	
J	0.42	1.42	0.190	0.0471	J	0.03	1.03	0.444	0.0746	J	0.09	1.09	0.323	0.0606	F	0.2	1.2	0.364	0.0627	I	0.53	1.53	0.211	0.0413	
F	0.33	1.33	0.143	0.0354	G	0.51	1.51	0.294	0.0494	H	0.44	1.44	0.225	0.0421	H	0.2	1.2	0.303	0.0522	J	0.27	1.27	0.166	0.0325	
I	0.33	1.33	0.107	0.0266	B	0.3	1.3	0.226	0.0380	G	0.17	1.17	0.192	0.0360	J	0.33	1.33	0.228	0.0393	C	0.69	1.69	0.098	0.0192	

suppliers, the critical criteria's final weights were arranged in descending order of importance. The graphical representation of criteria priorities is illustrated in Fig. 7.

It is observed that Criterion A (Proper manufacturing and supply capabilities) and Criterion D (Capacity to establish supply networks in the downstream), with relative weights of 0.1624 and 0.1583, respectively, emerged as the most crucial criteria for tier-1 supplier selection. These two criteria are particularly valuable in practical evaluations. A supplier is deemed to be in the first tier if it can manufacture and deliver components required by a major OEM, while also managing a network of its sub-suppliers. Based on priorities and expert opinions, the current key factors seem to be accurately recognized, highlighting the significance of focusing on these selection criteria for tier-1 suppliers.

4.3 Criteria prioritization by the borda method

In this section, we summarize the results from the experts' opinions shown in Table 3 using the Borda method. Here, the values provided by the experts in Tables 3 and 4 are considered as the rankings given by the voters. These consolidated opinions are presented in Table 7. Table 8 shows the ranking results for each criterion and its final rank.

Figure 8 displays the priority order of tier-1 supplier selection criteria obtained using the Borda method.

All six practitioners emphasised that Tier-1 suppliers must demonstrate not only consistent production volumes but also rigorous process controls and flexibility. As one procurement director noted, "In automotive assembly, any deviation, even a 0.5 mm tolerance shift, can shut a line. Suppliers with validated quality systems (e.g., SPC, ISO/TS 16949) and scalable capacity keep us running." An operations manager added, "During peak seasons, we rely on our Tier-1 s to ramp up by 20–30% within weeks; without robust manufacturing capabilities, we simply cannot meet customer demand.

Experts agreed that a supplier's own network of sub-suppliers and logistics partners critically shapes resilience. As one sourcing specialist explained, "A tier-1 supplier is not just a parts maker; it orchestrates a network of tier-2 suppliers and carriers. If they cannot secure raw materials or transport in the event of a disruption, our entire chain stalls." Another expert observed, "Post-pandemic shortages taught us that suppliers with diversified, geographically balanced downstream networks rebounded faster and shielded us from single-region shocks.

4.4 Comparative analysis

To further validate the robustness of our criterion-weighting framework, we introduce two well-established MCDM methods; i.e., AHP and BWM, alongside our existing Borda and SWARA approaches. AHP, with its emphasis on pairwise comparisons and consistency checks, provides a rigorous check on relative criterion intensities, while BWM reduces cognitive load and yields reliability measures with fewer comparisons through requiring experts to identify only the most and least important criteria. By comparing weights derived from these four methods, we can assess whether the final ranking of sustainability criteria (and, by extension, the tier-1 suppliers) is method-dependent or exhibits broad stability. This comparative analysis not only addresses concerns about potential methodological bias but

Table 6 Calculations of the final criteria weights for tier-1 supplier selection

Criteria	E1	E2	E3	E4	E5	E6	Weighted geometric mean	Normalized final weights
A	0.1455	0.2483	0.1680	0.1875	0.1040	0.0973	0.1503	0.1624
B	0.1177	0.0822	0.0380	0.1785	0.1290	0.1585	0.1050	0.1135
C	0.1412	0.1826	0.1101	0.0881	0.1721	0.0192	0.0969	0.1047
D	0.0956	0.1449	0.1514	0.1580	0.1579	0.1886	0.1464	0.1583
E	0.1099	0.0953	0.1442	0.1137	0.0752	0.1961	0.1168	0.1262
F	0.0583	0.0354	0.1090	0.0694	0.0627	0.1148	0.0695	0.0751
G	0.1165	0.0708	0.0494	0.0360	0.0759	0.0632	0.0643	0.0695
H	0.0793	0.0668	0.0769	0.0421	0.0522	0.0885	0.0655	0.0708
I	0.0432	0.0266	0.0784	0.0661	0.1316	0.0413	0.0565	0.0610
J	0.0928	0.0471	0.0746	0.0606	0.0393	0.0325	0.0542	0.0585

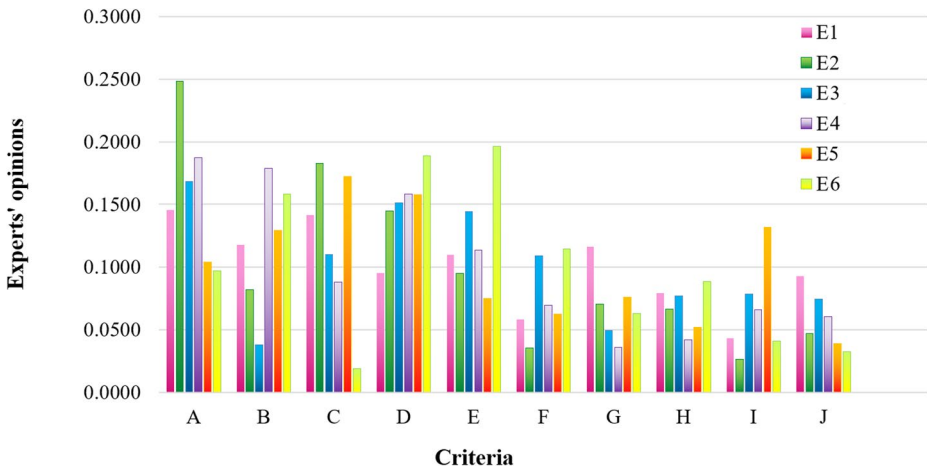


Fig. 6 Comparative analysis of expert opinions for selection criteria of tier-1 suppliers

also demonstrates the extent to which ordinal versus cardinal aggregation influences final decision outcomes.

- *AHP method* Each expert constructs a full 10×10 pairwise comparison matrix, using Saaty’s 1–9 scale to express the relative importance of each criterion. Individual matrices are aggregated via the geometric mean to form a single consensus matrix. We then compute its principal eigenvector to obtain criterion weights, verifying consistency through the Consistency Ratio (CR), with a threshold of 0.10. This process ensures that the final AHP weights reflect both intensity and overall agreement among experts.
- *BWM* For each expert, we first identify the single most important (best) and single least important (worst) criterion among the ten. The expert then provides pairwise comparisons of the best criterion versus all others (Best-to-Others vector) and of all others versus the worst criterion (Others-to-Worst vector), again on a 1–9 scale. We solve a linear programming model to minimize the maximum absolute deviation between these

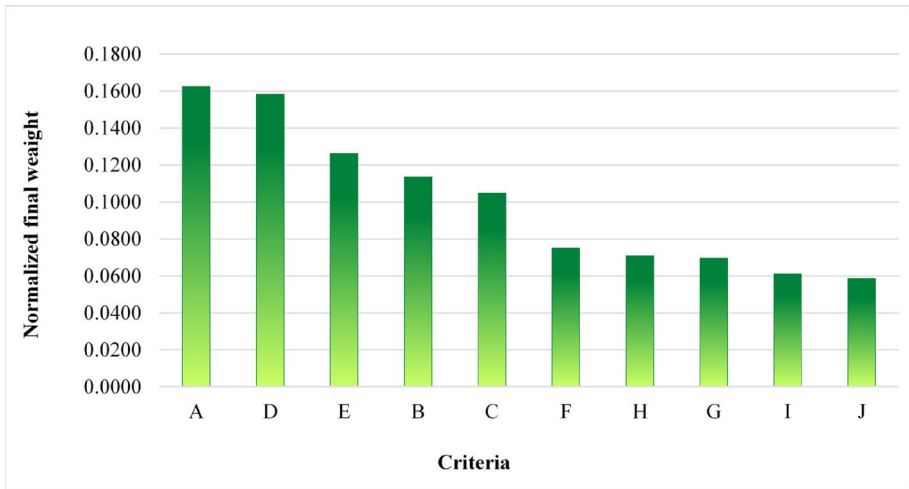


Fig. 7 Prioritization of the critical criteria in the tier-1 supplier selection process

Table 7 Ranking of the criteria for tier-1 supplier selection, presented by experts

	E1	E2	E3	E4	E5	E6
A	A	A	A	A	C	E
C	C	C	D	B	D	D
B	D	D	E	D	I	B
G	E	E	C	E	B	F
E	B	B	F	C	A	A
D	G	G	I	F	G	H
J	H	H	H	I	E	G
H	J	J	J	J	F	I
F	F	F	G	H	H	J
I	I	I	B	G	J	C

Table 8 Ranking of the criteria by the Borda method

Criteria	E1	E2	E3	E4	E5	E6	Sum	Final rank
A	1	1	1	1	5	5	14	1
B	3	5	10	2	4	3	27	5
C	2	2	4	5	1	10	24	4
D	6	3	2	3	2	2	18	2
E	5	4	3	4	7	1	24	3
F	9	9	5	6	8	4	41	6
G	4	6	9	10	6	7	42	7
H	8	7	7	9	9	6	46	9
I	10	10	6	7	3	8	44	8
J	7	8	8	8	10	9	50	10

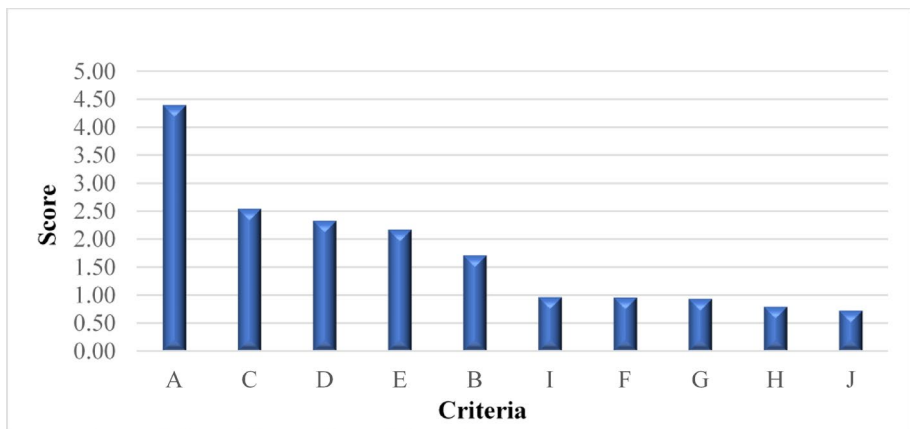


Fig. 8 Prioritization of the critical criteria in the tier-1 supplier selection process: Borda method

comparisons and the implied weight ratios, producing a weight vector and a consistency index for each expert. Aggregating these individual BWM weight vectors (via arithmetic mean) yields the final BWM weights, balancing reduced comparison burden with built-in consistency assessment.

In the AHP stage, each of the six experts is asked to complete a full 10×10 pairwise comparison matrix for the criteria that is presented in Table 9. Once all individual pairwise comparison matrices are collected, we aggregate them into a single consensus pairwise comparison matrix by computing the geometric mean of corresponding entries across the six matrices. The aggregated pairwise comparison matrix is shown in Table 10. Finally, we calculate the CR of the aggregated pairwise comparison matrix to ensure $CR \leq 0.10$, and it is observed that $CR = 0.07$. Consequently, the weights of the 10 criteria are presented in Table 10.

For the BWM stage, each expert first identifies the single “best” (most important) and “worst” (least important) criterion among the 10. The expert then provides a Best-to-Others vector by comparing the best criterion against each of the remaining nine on a 1–9 scale, and an Others-to-Worst vector by comparing each of the other 9 criteria against the worst criterion, again on a 1–9 scale, and the evaluations are shown in Table 11. To compute each expert’s BWM weight vector, we solved a linear optimization problem that minimizes the maximum absolute discrepancy between the implied weight ratios and the expert’s stated comparisons. Once each expert’s individual weight vector (and associated consistency metric) is obtained, we aggregate the 8 weight vectors by arithmetic mean to produce the final group BWM weight vector (Table 12).

Table 13 represents a comparison of the rankings obtained from the SWARA, Borda, AHP and BWM methods. It can be seen that the rankings differ between the methods, but the changes in rankings are relatively close.

As can be seen, the ranking differences are also very close, with no significant discrepancies between them. The level of correlation between these four rankings, shown in Table 14, further indicates that the methods produced closely aligned rankings for this issue.

In summary, the four weighting methods (Borda, SWARA, AHP, and BWM) produce largely convergent criterion hierarchies, with Spearman’s rank correlation coefficient

Table 9 Pairwise comparison matrix for each expert

	A	B	C	D	E	F	G	H	I	J
A	(1, 1, 1, 1, 1)	(8, 9, 7, 6, 8, 7)	(4, 4, 3, 3, 3, 4)	(2, 3, 2, 2, 2, 3)	(6, 6, 5, 4, 5, 5)	(9, 9, 9, 8, 9, 8)	(9, 8, 9, 8, 9, 7)	(9, 9, 9, 8, 9, 9)	(9, 9, 9, 8, 9, 9)	(9, 9, 9, 8, 9, 9)
B		(1, 1, 1, 1)	(0.25, 0.2, 0.33, 0.33, 0.2)	(0.17, 0.17, 0.25, 0.2, 0.2)	(0.5, 0.33, 0.5, 0.5, 0.5)	(2, 3, 2, 2, 2, 3)	(4, 4, 3, 3, 3, 4)	(6, 7, 5, 4, 5, 5)	(8, 8, 7, 6, 8, 8)	(9, 9, 9, 8, 9, 9)
C			(1, 1, 1, 1, 1)	(0.5, 0.5, 0.5, 0.17)	(2, 4, 2, 2, 2, 3)	(5, 5, 5, 4, 5, 5)	(8, 9, 7, 6, 8, 8)	(9, 9, 9, 8, 9, 8)	(9, 9, 9, 8, 9, 8)	(9, 9, 9, 8, 9, 9)
D				(1, 1, 1, 1, 1)	(3, 3, 3, 3, 3, 3)	(8, 7, 7, 6, 8, 7)	(6, 9, 9, 8, 9, 9)	(9, 8, 9, 8, 9, 8)	(9, 9, 9, 8, 9, 9)	(9, 7, 9, 8, 9, 7)
E					(1, 1, 1, 1, 1)	(4, 4, 3, 3, 3, 4)	(6, 6, 5, 4, 5, 6)	(8, 8, 7, 6, 8, 8)	(9, 9, 9, 8, 9, 9)	(9, 8, 9, 8, 9, 8)
F						(1, 1, 1, 1, 1)	(2, 3, 2, 2, 2, 3)	(4, 1, 3, 3, 3, 1)	(6, 2, 5, 4, 5, 2)	(8, 3, 7, 6, 8, 3)
G							(1, 1, 1, 1, 1)	(2, 0.5, 1, 2, 2, 0.5)	(4, 2, 2, 3, 3, 2)	(6, 2, 3, 4, 5, 3)
H								(1, 1, 1, 1, 1)	(2, 2, 1, 2, 2, 2)	(4, 2, 2, 3, 3, 3)
I									(1, 1, 1, 1, 1)	(2, 0.33, 3, 2, 2, 0.5)
J										(1, 1, 1, 1, 1, 1)

Table 10 Aggregated pairwise comparison matrix for each expert and the results of AHP

	A	B	C	D	E	F	G	H	I	J	Weights
A	1.00	7.44	3.46	2.29	5.12	8.65	8.30	8.83	8.83	8.74	0.3077
B	0.13	1.00	0.27	0.20	0.47	2.29	3.46	5.25	7.46	8.74	0.0796
C	0.29	3.75	1.00	0.42	2.40	4.82	7.61	8.65	8.65	8.74	0.1571
D	0.44	5.09	2.40	1.00	3.00	7.13	8.25	8.49	8.83	8.21	0.2117
E	0.20	2.14	0.42	0.33	1.00	3.46	5.28	7.46	8.83	8.49	0.1123
F	0.12	0.44	0.21	0.14	0.29	1.00	2.29	2.18	3.66	5.63	0.0456
G	0.12	0.29	0.13	0.12	0.19	0.44	1.00	1.12	2.57	3.46	0.0293
H	0.11	0.19	0.12	0.12	0.13	0.46	0.89	1.00	1.78	2.63	0.0244
I	0.11	0.13	0.12	0.11	0.11	0.27	0.39	0.56	1.00	1.41	0.0172
J	0.11	0.11	0.11	0.12	0.12	0.19	0.28	0.36	0.79	1.00	0.0152

$\rho > 0.84$ between any pair of ranking vectors. Notwithstanding this overall stability, SWARA, AHP, and BWM tend to assign slightly higher priority to the first two top criteria about supply-chain/logistics capabilities: both deal with managing the flow of goods; Criterion A at the production/upstream end and Criterion D at the distribution/downstream end, while Borda's best-second criterion highlights the ability to harness collaboration for new product development.

Table 11 Comparison matrix of the criteria

	Worst criterion										
	Best criterion	A	B	C	D	E	F	G	H	I	J
E1	A	1	9	5	3	7	8	6	4	2	9
E2	A	9	6	8	9	7	5	4	3	2	1
E3	A	1	7	4	2	5	9	8	6	3	9
E4	A	9	5	7	8	6	4	3	2	9	1
E5	A	1	8	6	4	2	3	5	7	9	9
E6	A	9	7	8	6	5	4	3	2	1	1
		1	3	9	5	7	2	4	6	8	9
		9	4	8	7	6	5	3	2	1	1
		1	5	3	2	4	6	7	8	9	9
		9	6	7	8	5	4	3	2	1	1
		1	5	3	2	4	6	7	8	9	9
		9	5	7	8	6	4	3	2	1	1

In particular, SWARA and AHP show the strongest agreement ($\rho = 0.9515$), indicating that experts' numeric judgments were already largely consistent with AHP's pairwise eigenvector results. Borda's pure ordinal aggregation aligns closely with AHP ($\rho = 0.9152$) and with SWARA ($\rho = 0.8424$), while BMW's best–worst optimization also correlates well with both SWARA ($\rho = 0.8424$) and AHP ($\rho = 0.8545$). The slightly lower correlations between purely ordinal (Borda) or simplified (BMW) methods and the fully numerical ones reflect minor reordering among near-tie criteria, but none of these shifts alter the overall hierarchy in a meaningful way.

Below is a summary of how Borda differs from SWARA alone and why Borda's inclusion is essential:

1. Using SWARA Outputs as Borda Rankings

Rather than soliciting fresh rankings, we took each expert's SWARA-derived weight vector (i.e., the numeric importance scores in Tables 3 and 4) and converted those into ordinal rankings. Each table entry effectively became a “vote” in the Borda count. This ensures that Borda respects the same underlying expert judgments without requiring additional meetings.

2. Weight Differences and Rank Shifts

Comparing the pure SWARA weights with the Borda weights (points assigned according to experts' SWARA-based rank orders), we found that 8 out of 10 criteria shifted by at least one position (Table 12). For example, the ability to harness collaboration for new product development (C) moved from 5th place under SWARA alone (weight=0.047) to 2nd place under Borda. Although SWARA's numeric average for C was modest, 3 out of 6 experts actually ranked C among their top three; moreover, Borda preserves that ordinal consensus.

3. Spearman Correlation

The rank-order correlation between SWARA and Borda is high ($\rho = 0.84$), indicating overall stability. This stability suggests that the inclusion of the Borda method does not significantly alter the rankings produced by SWARA alone. Consequently, practitioners can confidently utilize either method in decision-making processes without substantial discrepancies in outcomes.

All in all, by taking the initial SWARA assessments as inputs for Borda, we preserved all expert judgments while avoiding redundant data collection. The comparative analysis (Sub-Sect. 4.4) demonstrates that Borda's inclusion significantly refines consensus weights, particularly in borderline cases, and has a tangible impact on supplier selection. Therefore, integrating Borda into SWARA is methodologically justified and enhances decision-making rigor.

4.5 Clustering of the criteria

K-Means clustering is an unsupervised Machine Learning (ML) algorithm that partitions data into distinct groups based on similarity (Ezugwu et al., 2022). PCA is also a dimensionality reduction technique that transforms high-dimensional data into a smaller set of

Table 12 Weights of the criteria obtained by the BWM

Criteria	E1	E2	E3	E4	E5	E6	Weights
A	0.2069	0.2065	0.2073	0.2079	0.2049	0.2049	0.2064
B	0.0460	0.0590	0.0518	0.1386	0.0820	0.0820	0.0766
C	0.0828	0.1032	0.0691	0.0462	0.1366	0.1366	0.0958
D	0.1379	0.2065	0.1036	0.0831	0.2049	0.2049	0.1568
E	0.0591	0.0826	0.2073	0.0594	0.1025	0.1025	0.1022
F	0.0517	0.0459	0.1382	0.2079	0.0683	0.0683	0.0967
G	0.0690	0.0516	0.0829	0.1039	0.0585	0.0585	0.0708
H	0.1035	0.0688	0.0592	0.0693	0.0512	0.0512	0.0672
I	0.2069	0.1377	0.0461	0.0520	0.0455	0.0455	0.0889
J	0.0362	0.0382	0.0345	0.0318	0.0455	0.0455	0.0386

Table 13 Ranking of the criteria using all methods

Criteria	Borda	SWARA	AHP	BWM
A	1	1	1	1
B	5	4	5	7
C	2	5	3	5
D	3	2	2	2
E	4	3	4	3
F	7	6	6	4
G	8	8	7	8
H	9	7	8	9
I	6	9	9	6
J	10	10	10	10

Table 14 Correlation between the ranks provided by comparative analysis

	Borda	SWARA	AHP	BWM
Borda	1	0.8424	0.9152	0.8545
SWARA		1	0.9515	0.8424
AHP			1	0.8545
BWM				1

uncorrelated variables called principal components (Xie et al., 2024). The clustering results obtained using the K-Means clustering algorithm after reducing the data with PCA provide a meaningful grouping of the criteria based on their rankings from six experts, Borda, and SWARA methods. The final cluster assignments, as illustrated in Fig. 9, show that the 10 criteria are divided into three distinct groups. Cluster 0 includes Criteria A, D, and E, indicating that these criteria share similar patterns in how they were ranked across the different methods. These criteria are positioned close to each other in the PCA plot, suggesting that they may represent a common theme or level of importance.

According to Fig. 9, we realize that

1. *Cluster 1 consists of the largest number of criteria, including F, G, H, I, and J* This group forms a dense region in the visualization, showing that these criteria are relatively consistent in terms of their aggregated ranking behavior. They appear to be more

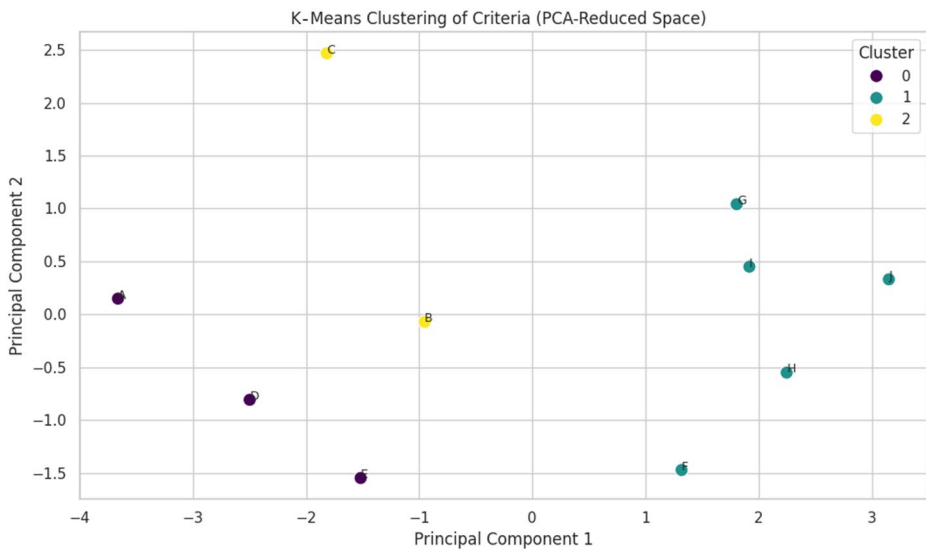


Fig. 9 Clustering of the criteria

closely related to each other than to any other criteria, which could imply that they represent another shared category or priority level in the evaluation process.

2. *Cluster 2 contains only two criteria, including B and C* These two are placed separately in the PCA plot, indicating that their ranking profiles differ significantly from those in the other clusters. While they are grouped together, their placement suggests that they may represent a unique or transitional set of criteria that stand apart from the rest.

The PCA visualization complements the clustering by projecting the original eight-dimensional data (6 experts, SWARA, and Borda results) into two dimensions, making it easier to interpret the relationships between criteria. The plot shows a clear separation between the clusters, supporting the choice of three as a reasonable number of clusters for this dataset. From a practical standpoint, these clusters can help in understanding which criteria behave similarly across expert opinions and aggregation techniques. This insight can support decision-making by identifying patterns, prioritizing groups of criteria, or simplifying complex multi-criteria evaluations.

5 Discussion: practical and theoretical implications

The study endeavors to provide actionable insights for managerial decision-making in the context of sustainable tier-1 supplier selection. Through a systematic research process, the study identifies and prioritizes selection criteria crucial for optimizing supplier relationships. The methodologies employed, including the Delphi method, fuzzy logic, and the SWARA method, offer practical avenues for streamlining decision-making processes and enhancing supplier selection outcomes.

Managers tasked with supplier selection processes can benefit from adopting the Delphi method, which facilitates collaborative problem-solving among experts from diverse backgrounds. By leveraging the collective wisdom of experts, managers can gain valuable insights into critical selection criteria while minimizing administrative overheads. Furthermore, the integration of fuzzy logic into the decision-making process enables managers to navigate the inherent uncertainty in supplier selection. By converting linguistic expressions into fuzzy numbers, managers can make informed decisions based on nuanced interpretations of imprecise data. This approach not only enhances the robustness of decision outcomes but also mitigates the risk of overlooking crucial factors due to uncertainty.

The SWARA method, with its emphasis on evaluating and weighting alternatives, offers managers a structured approach to prioritize selection criteria. By engaging in expert consultations and assessing the accuracy of attribute weights, managers can make more informed decisions regarding supplier selection. This methodological approach not only enhances the precision of decision outcomes but also fosters confidence in the selection process among stakeholders. Overall, by leveraging innovative methodologies such as the Delphi method, fuzzy logic, and the SWARA method, managers can streamline supplier selection processes, optimize supplier relationships, and ultimately drive organizational performance. The insights gleaned from this study offer tangible pathways for managers to enhance their decision-making capabilities and achieve strategic objectives in supplier management.

In practice, the weighted sustainability criteria generated by our Fuzzy Delphi-Borda-SWARA model can be embedded directly into a company's supplier-evaluation and management systems to drive more transparent, data-driven decisions at every stage of the tier-1 sourcing process. Specifically, procurement teams can

- *Build Weighted Scorecards* Import the final weight vector into existing scorecard templates or SRM software so that each supplier's performance on environmental compliance, cost stability, manufacturing capability, downstream network strength, and other top criteria is multiplied by its agreed importance. This ensures that overall supplier scores reflect both the organization's strategic priorities and the consensus judgment of its experts.
- *Prioritize Due Diligence and Audits* Focus audit resources on criteria with the highest weights (e.g., proper manufacturing capabilities and downstream network resilience), scheduling deeper on-site inspections or third-party verifications where they matter most.
- *Stratify and Manage Suppliers* Use weighted scores to segment suppliers into "preferred," "conditional," and "development" tiers, then allocate relationship management efforts accordingly (e.g., strategic partnerships for top scorers, targeted improvement plans for mid-range performers).

Our study suggests that firms should first concentrate their supplier analysis on the most relevant factors; e.g., possessing robust manufacturing capability, having effective downstream networks, and having a demonstrated capacity to innovate, enabling supplier selection to effectively align with and support broader strategic objectives. Through a process of utilizing a diverse team of cross-functional specialists, companies can draw on different perspectives and create true consensus regarding what criteria are most critical, as well as create stakeholder buy-in. Where data are incomplete or uncertain, fuzzy-logic approaches

enable decision makers to quantify and aggregate linguistic evaluations without oversimplification and with increased confidence in complex judgments. To translate such comprehension into explicit, reproducible outcomes, accepting the SWARA approach enables systematic stepwise weighting of single criteria, increasing the level of rigor and transparency within the weighting. To this, adding a Delphi-reduced method accelerates decision-making further, cuts administrative time, and ensures that expert opinion is added in an effective manner. With pre-set weights for criteria, it is then imperative that potential suppliers not only achieve these levels of performance but also the same fundamental values and long-term aims of the organization, thereby reinforcing partnerships and mitigating supply-chain risk. Sustained innovation, whether in the exploration of new analytic methodologies or the integration of real-time data, allows the supplier-selection process to remain nimble in rapidly evolving markets. Of no lesser importance is a spirit of continuous improvement: revisiting and refining both criteria and processes on a regular basis, as triggered by performance metrics and stakeholder feedback, keeps supplier management responsive and efficient. To complement this, firms need to make investments in building internal capability, via training or hiring, to effectively carry out advanced methodologies. Finally, through the utilization of efficient performance-monitoring systems, which track the performance of suppliers against set standards, organizations can identify areas for improvement, optimize operational efficiency, and preserve competitive superiority over the long term.

Additionally, to translate our findings into actionable guidance, companies can embed the final criterion weights directly into their supplier evaluation and management systems to drive decision making at multiple levels. For example, procurement teams should update their supplier scorecards or SRM dashboards to reflect the high priority assigned to Criterion A (Proper Manufacturing and Supply Capabilities) and Criterion D (Capacity to establish supply networks in the downstream), ensuring that any new or existing tier-1 candidate is evaluated first on its demonstrated quality control systems, scalable capacity, and process-flexibility metrics, and second on the robustness and geographic diversity of its own sub-supplier and logistics networks. By weighting these dimensions most heavily, organizations can prioritize supplier development programs (e.g., joint capability audits, investment in production line upgrades) and risk-mitigation measures (e.g., dual-sourcing or collaborative planning with suppliers who have strong downstream partnerships) where they matter most. Furthermore, integrating these weights into routine quarterly business reviews empowers cross-functional teams (procurement, quality, sustainability) to monitor performance against the criteria that experts agree are critical, trigger early-warning alerts when scores dip below thresholds, and align contract incentives (e.g., bonus payments or penalty clauses) with the weighted criteria; thereby closing the loop between strategic priorities and day-to-day supplier management.

Our contributions to the three major research gaps can be reviewed as follows:

Gap 1 Insufficient Handling of Uncertainty in Criterion Screening

- *Description:* Many sustainable-supplier studies rely on crisp expert judgments, which overlook the inherent vagueness of linguistic assessments.
- *Our Contribution:* By introducing a Fuzzy Delphi stage, we transform linguistic inputs (“high,” “medium,” “low”) into fuzzy numbers and apply convergence thresholds to filter out inconsistent or marginal criteria. This fills the gap by providing a rigorous, uncertainty-aware screening before any numeric weighting.

Gap 2 Lack of Hybrid Aggregation Methods Mitigating Expert Bias

- *Description:* Traditional weighting approaches, such as AHP, BWM, and SWARA, as well as fuzzy-TOPSIS, typically establish the criteria based on the findings of literature reviews.
- *Our Contribution:* We integrate SWARA's efficient numeric elicitation with Borda's ordinal aggregation, ensuring that (i) expert effort remains low, (ii) magnitude and rank-order consensus are both respected, and (iii) numeric outliers cannot unduly skew weights. This hybrid fills the methodological void by balancing cardinal and ordinal aggregation in a single streamlined workflow.

Gap 3 Limited Comparative Validation Across MCDM Frameworks

- *Description:* Although various methods (e.g., AHP, BWM, VIKOR, TOPSIS) are routinely applied, there is a dearth of studies conducting head-to-head comparisons to demonstrate robust convergence or divergence in supplier rankings.
- *Our Contribution:* We perform a detailed comparative analysis, including Spearman correlations among SWARA, SWARA+Borda, AHP, and BWM, as well as supplier-ranking shifts, showing that our hybrid weights not only align with established techniques ($\rho \geq 0.84$) but also, in borderline cases, yield more defensible outcomes (e.g., disambiguating tied supplier scores). This validation addresses the gap by empirically demonstrating method robustness and the practical impact of weight elicitation choices on sustainability-focused supplier selection.

6 Conclusion and future work

The classification and tiering of suppliers have gained significant attention from manufacturers worldwide. Supplier tiering offers several notable advantages, including enhanced management associations, reduced costs for OEMs, and the potential for work specialization, leading to improved product quality. Given these benefits, contemporary manufacturers are progressively adopting tiering as a fundamental organizational principle for structuring their supply chain systems. However, pivotal questions arise regarding the classification of sustainable suppliers into tier-1 status and the requisite characteristics they should possess. To address these important issues, the current study developed a comprehensive decision-making approach. Initially, a list of 35 criteria impacting supplier tiering was derived through a rigorous review of the literature. Subsequently, employing the fuzzy Delphi technique, 10 essential criteria were recognized as crucial for sustainable tier-1 supplier selection. Additionally, the Borda method and SWARA technique were employed to prioritize these critical criteria and assess their respective impacts on the final selection of sustainable tier-1 suppliers. Notably, criteria such as proper manufacturing and supply capabilities (Criterion A) and capacity to establish supply networks in the downstream (Criterion D) emerged as the most important for tier-1 supplier selection. Closely following were criteria related to the ability to produce modules (Criterion E), practical knowledge of manufacturing processes (Criterion B), and the ability to harness collaboration for new product development (Criterion C). Furthermore, factors such as trust between tier-1 suppliers and OEMs, infrastructure

adequacy, acceptable innovations, and guarantees in produced components were identified as additional important considerations in the tiering process. The findings presented herein offer valuable insights into tiering major suppliers, selecting tier-1 suppliers, and evaluating their subsequent performance. Nevertheless, given the qualitative nature of certain criteria, the application of fuzzy numbers is warranted to address the complexities inherent in MADM methods. This robust approach ensures a comprehensive evaluation framework, enabling managers to make informed decisions amidst uncertainty and variability in supplier characteristics.

Importantly, this study went beyond traditional prioritization by incorporating comparative analysis across multiple weighting techniques; i.e., SWARA, SWARA+Borda, AHP, and BWM. By evaluating rank stability using Spearman correlation coefficients and analyzing rank shifts, we demonstrated the robustness of the proposed hybrid Fuzzy Delphi-Borda-SWARA model. This head-to-head comparison provided empirical validation of the model's consistency and reliability for sustainable supplier selection. Additionally, the implicit clustering of the finalized criteria—grouping them into operational capabilities, collaboration and innovation, trust and relationship strength, and infrastructure—enhanced the interpretability and applicability of the results for supply chain managers. This functional clustering facilitates the development of targeted improvement strategies in tier-1 supplier relationships.

In this work, we performed the analysis under the assumption of criteria independence. However, it is conceivable to construct a network of interrelated criteria using the DEMATEL method or other MADM models to provide a detailed comparative analysis. Such approaches would not only facilitate the selection of primary suppliers within specific industries but also aid in recognizing criteria relevant to various industrial sectors and geographic regions. Looking ahead, this methodology holds strong potential for adaptation beyond the automotive sector. Future research may explore dynamic criteria evaluation, real-time data integration, or intelligent decision-support systems combining expert knowledge with ML. These advancements can further improve the applicability and scalability of the framework across global and multi-tier supply chains.

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