Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Issue 4, October 2025
DOI : https://doi.org/10.33395/sinkron.v9i4.15261
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Optimizing Supplier Selection Through Hybrid BWM and AHP Integration

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Submitted :Aug 22, 2025 | **Accepted** : Sep 21, 2025 | **Published** : Oct 2, 2025

Abstract: This study proposes a hybrid decision-making model that integrates the Best-Worst Method (BWM) with the Analytic Hierarchy Process (AHP) to optimize supplier selection. The primary objective is to address limitations in traditional Multi-Criteria Decision-Making (MCDM) methods, such as inconsistency, subjectivity, and cognitive overload when handling complex criteria. The proposed model leverages AHP's hierarchical structuring and BWM's efficiency in reducing comparison load, aiming for a more accurate and consistent evaluation framework. The research design involves developing a hybrid AHP-BWM model and applying it to a dataset from the Vietnamese Textile and Apparel (T&A) sector. The methodology includes two stages: determining the weight of each criterion using a Hesitant-AHP approach, followed by evaluating supplier alternatives with BWM. The performance of the model is assessed using classification metrics, namely accuracy, precision, recall, and F1-score. The results show that the proposed model outperforms conventional methods such as TOPSIS, ELECTRE, VIKOR, and SWARA. It achieves an accuracy of 92%, precision of 87%, recall of 86%, and an F1-score of 86%. These outcomes confirm the model's superior ability to consistently classify supplier suitability. Furthermore, the model identifies Quality Assurance as the most critical criterion, followed by Assistance, Capacity, Charge, and Shipment. In conclusion, the hybrid AHP-BWM model offers a robust, scalable, and data-driven approach for supplier selection. Its strength lies in balancing systematic evaluation with reduced cognitive effort, making it suitable for complex real-world decision-making environments. Future research may explore its application in other domains and enhance its scalability for larger datasets.

Keywords: BWM; AHP; MCDM; Hybrid Model; Decision Making

INTRODUCTION

Supplier selection plays a pivotal role in the success of organizations, influencing everything from cost efficiency to product quality and delivery times(Jefroudi & Darestani, 2024). With the increasing complexity of global supply chains, selecting the right supplier has become a multi-dimensional decision-making process that requires the careful evaluation of various criteria(Xiang & Zhang, 2025). Over the years, numerous Multi-Criteria Decision-Making (MCDM) methods have been proposed for supplier selection(Wang et al., 2020), including Analytical Hierarchy Process (AHP)(Manik, 2023), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)(Kamalakannan et al., 2020), PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations)(Tong et al., 2022), VIKOR (Vlse Kriterijumska Optimizacija I Kompromisno Resenje)(Oliveira et al., 2023a), and ELECTRE (Elimination Et Choix Traduisant la Realité)(Salvador et al., 2024).

While each of these methods has been widely used in various decision-making contexts(Carpitella et al., 2024), they also exhibit certain limitations, particularly in complex and large-scale decision-making environments(Lin et al., 2024). The Analytical Hierarchy Process (AHP) is one of the most widely used methods for multi-criteria decision-making(Carpitella et al., 2024). It allows decision-makers to structure complex problems into a hierarchy of criteria and sub-criteria, followed by pairwise comparisons to determine the relative importance of each criterion(Deretarla et al., 2023). While AHP is beneficial in terms of structuring decision problems, it suffers from inconsistencies when When analyzing multiple choices or evaluation dimensions (Pascoe, 2022). The increasing number of pairwise comparisons leads to decision-making fatigue and subjective biases, making it challenging to maintain consistency across large-scale problems(Dodevska et al., 2023). Additionally, AHP's reliance on

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pairwise comparisons can become cumbersome when dealing with a large set of criteria or alternatives, making it less practical for real-world applications involving numerous decision factors(Moslem, 2024).

TOPSIS, another widely used method, ranks alternatives based on their geometric distance from the ideal and negative-ideal solutions(Rahman et al., 2024). While TOPSIS is relatively straightforward and has been successfully applied in supplier selection, it relies heavily on the assumption that the decision-maker can accurately assess the distance between alternatives and ideal solutions(Tafazzoli et al., 2024). PROMETHEE, similarly, ranks alternatives by calculating preference indices, but it also suffers from the problem of subjectivity(Wątróbski, 2023). The decision-maker must provide weights for each criterion, which can lead to inconsistencies if the evaluator is not objective(Mufazzal et al., 2021). While both VIKOR and ELECTRE have been developed to address the shortcomings of the earlier methods, they still face challenges in handling complex decision scenarios with conflicting criteria and subjective judgments(Sitorus et al., 2019).

These traditional methods, while effective in certain scenarios, often exhibit limitations in terms of subjectivity, inconsistency, and cognitive load when applied to complex decision-making problems(Zheng et al., 2025). This paper proposes an integrated approach that combines the Best-Worst Method (BWM) and AHP to address these issues and improve the supplier selection process. Best-Worst Method (BWM) is a relatively newer method in the field of MCDM, offering a more efficient and precise way to determine the weights of criteria and alternatives. Unlike AHP, which requires a large number of pairwise comparisons, BWM reduces the number of comparisons by focusing on the best and worst alternatives(Aboutorab et al., 2018). This significantly enhances the consistency of the decision-making process, as the decision-maker is asked to make only a few key judgments. BWM has the advantage of being more systematic and less subjective than AHP, especially in problems where there are many criteria to evaluate(Pamučar et al., 2020). By focusing on the most extreme alternatives, BWM provides a clearer and more reliable way of determining the relative importance of each criterion or alternative(Tavana et al., 2023).

This is where AHP comes in. AHP provides a hierarchical structure for organizing decision criteria and alternatives, making it an effective tool for evaluating complex decisions with multiple levels of criteria(Ezzat & Hamoud, 2016). AHP allows decision-makers to assess criteria systematically, considering both tangible and intangible factors, and it can be used to handle large-scale decision problems in a structured manner(Kriswardhana et al., 2025). However, as mentioned earlier, AHP struggles with consistency and efficiency when dealing with numerous criteria. The integration of AHP and BWM leverages the strengths of both methods while addressing their individual weaknesses. By using AHP to accurately and consistently determine the weights of criteria and alternatives, and then applying BWM to evaluate and rank alternatives within a structured framework, the hybrid method significantly enhances the reliability, accuracy, and efficiency of the supplier selection process.

The synergy between AHP's precision in weight determination and BWM's comprehensive evaluation framework offers a robust solution to the challenges posed by complex decision-making problems. Furthermore, combining AHP and BWM reduces the subjectivity of the decision-making process, as BWM minimizes the need for numerous comparisons while ensuring consistency, and AHP provides a structured evaluation of alternatives. This integration makes the decision-making process more objective and data-driven, providing a balanced approach to supplier selection that mitigates the cognitive load and biases often associated with traditional MCDM methods.

Despite the extensive research on integrating MCDM methods, no study has specifically combined Hesitant-AHP with BWM to simultaneously reduce subjectivity and maintain consistency, particularly in the textile and apparel (T&A) sector, which is characterized by its highly dynamic and complex supply chain. This research gap highlights the need for a more robust and adaptive approach.

The objectives and main contributions of this paper are as follows:

1. To develop a hybrid model integrating Hesitant-AHP and BWM for supplier selection in the T&A sector.
2. To reduce subjectivity and bias in decision-making by incorporating Hesitant-AHP.
3. To enhance consistency and efficiency in criteria weighting through BWM.
4. To provide a more reliable and practical evaluation framework for decision-makers in the T&A industry.

LITERATURE REVIEW

Recent studies have increasingly focused on hybrid Multi-Criteria Decision-Making (MCDM) approaches, particularly the integration of the Best-Worst Method (BWM), Analytic Hierarchy Process (AHP), and other techniques for supplier selection. These hybrid models aim to overcome the weaknesses of single methods, such as subjectivity, inconsistency, and high cognitive load, by combining their complementary strengths.

Table 1. Recent Studies in Hybrid MCDM

Author(s)	Year	Method	Domain	Limitation
Aboutorab et al.	2018	Z-number BWM	Supplier development	Limited consideration of

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				complex hierarchies
Deretarla et al.	2023	AHP + COPRAS	Vendor selection	High potential for subjectivity remains
Debnath et al.	2023	SWARA + WASPAS	Healthcare supply chain	Limited generalizability across industries
Tavana et al.	2023	Interdependent BWM	Innovation assessment (NASA)	High computational complexity
Xiang & Zhang	2025	Hybrid DSS (AHP-based)	Global supply chain	Insufficient focus on reducing cognitive load

From the reviewed literature, no study has specifically integrated Hesitant-AHP with BWM to simultaneously reduce subjectivity and maintain consistency, particularly in the textile and apparel (T&A) sector.

Hesitant-AHP Method

The pseudocode of Hesitant-AHP Method as follows.

```
Algorithm 1: Hesitant AHP for Determining Weights of Criteria
Input: Set of Criteria $C$ – {Quality Assurance, Charge, Shipment, Assistance, Capacity}
Hesitant pairwise judgments matrix $Y$-$(y_{ij})$, where each $y_{ij}$ contains multiple values from 1-o scale (e.g., $y_{13} = \{3,4\}$);
Output: Weights vector $w = \{w_1, w_2, \dots, w_5\}$ for each criterion
Let $Y$= $(y_{ij})_{5x5}$ where each $y_{ij}$ is a hesitant set of values with equal or specified probabilities;
Use Monte Carlo sampling to generate $P$ comparison matrices $Y^{(l)}$ from $Y$;
for $l$= 1 to $P$ do
    Compute priority vector $w^{(l)}$ using row geometric mean method (RGMM)(;
    Compute $GCI^{(l)}$ using: $GCI$=$\frac{2}{(n-1)(n-2)} \sum_{i<j} log^2 \left(\frac{a_{ij} w_j}{w_i}\right)$;
end
Compute expected Geometric Consistency Index
    $E(GCI) = \frac{1}{P} \sum_{l=1}^{P} GCI^{(l)}$ ;
if $E(GCI) \leq threshold\ GCI(n)$ then
    Accept $Y$ as consistent;
Apply stochastic consistency improving procedure to obtain consisten $Y'$;
for $l$=1 to P do
    Generate matrix $Y^{(l)}$ from $Y$ using sampling;
    Compute priority vector $w^{(l)}$ using RGMM;
    Rank criteria from best to worst for each $w^{(l)}$;
    Count how often each criterion gets each rank → build rank acceptability index $b_i^T$;
end
DM sets attitudinal characer $AC(w) \in (0.5,1)$ and selects function $F(x)(e.g., F(x) = x^2)$;
Solve optimization to get aggregation weights $w_r$ using OWA;
Min $\sum_{r=1}^{n} F(w_r) s.t. \sum w_r = 1, w_r \geq 0, \sum \frac{n-r}{n-1} w_r = AC(w)$;
Compute holistic priority for each criterion $i$: $w_i = \sum_{r=1}^{n} w_r . b_i^r$;
Return $w$ as the final weights for each criterion
```

The provided algorithm describes a Hesitant Analytic Hierarchy Process (Hesitant AHP) designed to determine the weights of decision-making criteria under uncertainty. It begins by defining a set of criteria and constructing a Hesitant Comparison Matrix (HCM), where each element represents a hesitant judgment with multiple possible values on a 1–9 scale, reflecting ambiguity in expert preferences. To evaluate the consistency of these hesitant judgments, the algorithm uses Monte Carlo sampling to generate multiple crisp comparison matrices, calculates a priority vector using the Row Geometric Mean Method (RGMM), and then computes the Geometric Consistency Index (GCI) for each sample. The expected GCI is then compared to a predefined threshold to assess the overall consistency of the original hesitant matrix. If inconsistent, a stochastic consistency improvement method is applied. Once a consistent matrix is ensured, the algorithm performs a Hesitant Preference Analysis by repeating the sampling process and counting how often each criterion receives a certain rank, leading to the construction of a rank acceptability index. Finally, a weight aggregation procedure based on the Ordered Weighted Averaging (OWA) operator is applied, incorporating the decision maker's attitudinal character. This produces a holistic weight vector representing the final prioritization of each criterion, accommodating both hesitation in judgments and decision-maker preferences.

BWM Method

Best-Worst Method (BWM) in this study was used for determining the alternative weights per criterion in a MCDM process. The method takes a set of alternatives and criteria as inputs. For each criterion, the decision maker (DM) identifies the best and worst alternatives. Using these, two preference vectors are created: one for comparing the best alternative to others and one for comparing each alternative to the worst. The next step involves solving an optimization problem to determine the optimal weight vector for each criterion. The goal is to adjust the weights so that the ratios between the best and other alternatives, as well as between each alternative and the worst, match the given preference vectors. Additionally, the sum of all weights must be 1, and all weights must be non-negative. After solving the optimization problem, the optimal weight vector for each criterion is obtained. This process is repeated for all criteria, and the resulting weight vectors are returned as the output. The final output consists of the weight vectors for all the criteria, which represent the relative importance of the alternatives for each criterion. The pseudocode of BWM as follows.

```
Algorithm 2: Best-Worst Method (BWM) for Determining Alternative Weights per Criterion
Input:  Set of alternatives $A = \{A_1, A_2, \dots, A_n\}$
Set of criteria $C = \{C_1, C_2, .., C_m\}$
For each criterion $C_k$;
    -   Best Alernative $B_k$ and worst alternative $W_k$ identified by Decision Maker (DM)
    -   Best-to-others preference vector: $A_{B_k} = \left[a_{B_k1}, a_{B_k2}, \dots, a_{B_kn}\right]$
    -   Others-to-worst preference vector: $A_{B_k} = \left[a_{1W_k}, a_{2W_k}, \dots, a_{nW_k}\right]$
Output: Weiht vectors $w^{(k)} = \left[w_1^{(k)}, w_2^{(k)}, \dots w_n^{(k)}\right]$ for each criterion $C_k$
Foreach criterion $C_k \in C$ do
  Step 1: Identify the best $(B_k)$ and worst $(W_k)$ alternatives for criterion $C_k$;
  Step 2: Construct Best-to-Others vector $A_{B_k}$ where $a_{B_ki}$ indicates how much more important is
  compared $A_{B_k}$is compared to $A_i$;
  Step 3: Construct Others-to-Worst vector $A_{W_k}$where $a_i w_k$ indicates how much more important $A_i$
  is compared to $A_{W_k}$;
  Step 4: Solve the following optimization problem to obtain optimal weights;
  $\min_{\{w_i,\xi\}} \xi$
      $\left|\frac{w_{B_k}}{w_i} - a_{B_ki}\right| \leq \xi, \forall i \in \{1, \dots, n\}$
  $s.t. \left|\frac{w_i}{w_{W_k}} - a_i w_k\right| \leq \xi, \forall i \in \{1, \dots, n\}$
        $\sum_{i=1}^{n} w_i = 1, w_i \geq 0 \quad \forall i$
  Step 5: Let $w^{(k)} = \left[w_1^{(k)}, \dots, w_n^{(k)}\right]$ be the optimal weights obtained
end
return $w^{(k)}$ for all criteria $C_k$
```

METHOD

An outline of the research methodology can be seen in Figure 1.

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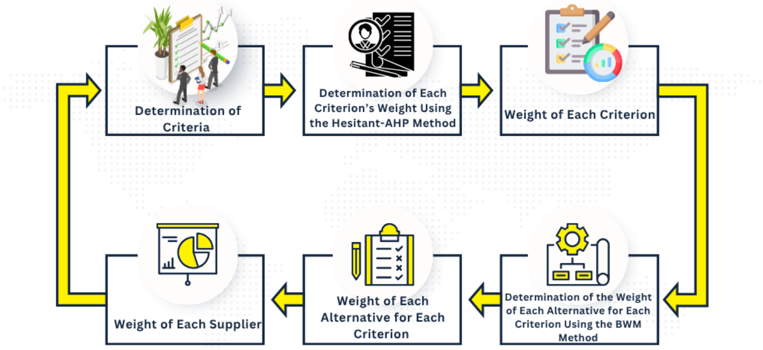

Figure 1. Research Step

Figure 1 illustrates a structured decision-making framework for evaluating and selecting suppliers Using an integrated set of MCDM methods to support complex evaluations. The process begins with the determination of criteria, where relevant evaluation factors are identified based on the objectives and requirements of the decision context. Following this, the weight of each criterion is calculated using the Hesitant Analytic Hierarchy Process (Hesitant-AHP) method, which accommodates uncertainty and hesitation in expert judgments. This results in a more flexible and realistic assessment of criterion importance. Next, the Best-Worst Method (BWM) is employed to determine the weight of each alternative (supplier) with respect to each criterion. This step helps in quantifying how well each supplier performs on individual criteria. Once the alternative weights are determined, the overall weight of each alternative for each criterion is aggregated. Finally, the process leads to the overall weight of each supplier, which reflects a comprehensive evaluation based on all selected criteria and alternative performances. This integrated approach ensures that supplier selection is carried out systematically, considering both subjective preferences and objective evaluations.

Performance Measurement

This study uses the Vietnamese T&A Sector dataset, which categorizes supplier selection with 64 features and 362 rows of data. This dataset provides in-depth information about the characteristics of suppliers in the T&A (Textile & Apparel) sector in Vietnam, with various features related to quality, price, production capacity, and other factors that influence supplier selection decisions(Nong, 2021).

The supplier selection features used in this study are quality assurance, charge, shipment, assistance, and capacity. The distribution of the data is presented in Table 1.

Table 1. Data Distribution

Category	Number of Instances
A decision has not been made; additional assessment is required.	339
This supplier is suitable for selection.	23

Table 1 shows the distribution of data based on the supplier selection decisions. A majority of the instances, 339 in total, fall under the category where a final decision has not been made yet, and further evaluation is required. This indicates that additional assessments are needed before making a conclusive choice. On the other hand, only 23 instances have been categorized as eligible for selection, meaning these suppliers are deemed suitable for selection without the need for further evaluation. This distribution highlights the importance of thorough evaluation in the decision-making process.

Preprocessing and Software

Before conducting the analysis, the dataset was preprocessed through several steps:

1. Data cleaning: removing empty rows, resolving duplicates, and handling missing values using median-based imputation.
2. Normalization: all numerical variables were normalized to the [0,1] range to ensure comparability across criteria.
3. Categorical encoding: categorical variables were transformed into numerical form using one-hot encoding.

All experiments were implemented using Python 3.10. The following libraries were applied: NumPy and Pandas for data processing, scikit-learn for performance evaluation (accuracy, precision, recall, and F1-score), and PuLP for solving the optimization model in BWM. Graphical visualization was performed using Matplotlib.

Dataset Selection and Limitations

The study employed the Vietnam Textile and Apparel (T&A) Supplier Selection Dataset published by Nong (2021). This dataset was selected because:

1. Relevance and authenticity: it reflects real-world supplier evaluation in Vietnam's textile and apparel industry, one of the most competitive and dynamic supply chains in Southeast Asia.
2. Rich features: it contains 64 attributes covering quality, cost, production capacity, logistics, and other decision-making factors aligned with the research objectives.
3. Public availability: the dataset is openly accessible, ensuring transparency and enabling reproducibility by other researchers.

Nevertheless, several limitations must be acknowledged:

1. Class imbalance – most of the records (339 out of 362) fall into the "undecided" category, while only 23 suppliers are classified as suitable, creating challenges for classification and evaluation.
2. Domain specificity – since the dataset focuses solely on Vietnam's T&A sector, the findings may not be directly generalizable to other industries or countries.
3. Contextual constraints – external factors such as government policies, international trade dynamics, or market fluctuations are not included in the dataset, which may limit the comprehensiveness of the analysis.

The performance will be calculated using Accuracy, Precision, Recall, and F1 Score. The comparison will be carried out by evaluating the performance of several methods, including Support TOPSIS(Haryono et al., 2024), ELECTRE(Jain & Singh, 2020), VIKOR(Oliveira et al., 2023b), and SWARA(Debnath et al., 2023), to determine the most effective approach. Performance measurement will be calculated using:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{FP+FN} \quad (3)$$

$$F1\ Score = 2 * \frac{Precision*recall}{Precision+Recall} \quad (4)$$

RESULT

Performance Calculation can be seen in Table 2.

Table 2. Perfomance Calcuation

Method	Accuracy	Precision	Recall	F1 Score
Proposed Method	0.92	0.87	0.86	0.86
TOPSIS	0.87	0.82	0.81	0.81
ELECTRE	0.84	0.76	0.74	0.75
VIKOR	0.78	0.68	0.67	0.67
SWARA	0.89	0.83	0.82	0.82

Table 2 shows that the hybrid Hesitant-AHP–BWM method outperforms other approaches with an accuracy of 92%, precision of 87%, recall of 86%, and F1-score of 86%. This improvement is primarily due to the combination of AHP's ability to structure criteria systematically and BWM's efficiency in reducing comparison load. The result is a more consistent and objective evaluation process compared to traditional methods such as TOPSIS, ELECTRE, VIKOR, and SWARA.

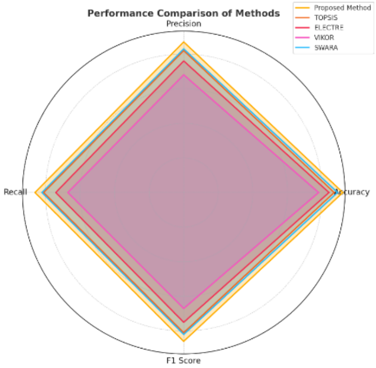

Figure 2. Performance Comparison Results

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Visualization in Figure 2 clearly demonstrates the hybrid method's superiority across all metrics, affirming its overall dominance. Figure 3 shows that *Quality Assurance* is the most important criterion (weight 0.4), followed by *Assistance* (0.2), *Capacity* (0.15), *Charge* (0.15), and *Shipment* (0.1). This finding aligns with the needs of the T&A industry, which heavily relies on quality standards to maintain global competitiveness.
For managers in the T&A industry, this study offers two main practical implications:

1. More efficient decision-making: With the reduced number of comparisons, the supplier selection process can be performed more quickly without sacrificing consistency.
2. Focus on critical factors: Emphasis on *Quality Assurance* and *Assistance* helps managers allocate resources to areas that most impact supply chain performance. This allows companies to reduce product quality risks and improve supplier reliability.

Overall, the hybrid method provides a practical, reliable, and scalable evaluation framework that can be directly implemented to improve supplier selection strategies in the T&A industry.

Comparison of criteria priorities can be seen in Figure 3.

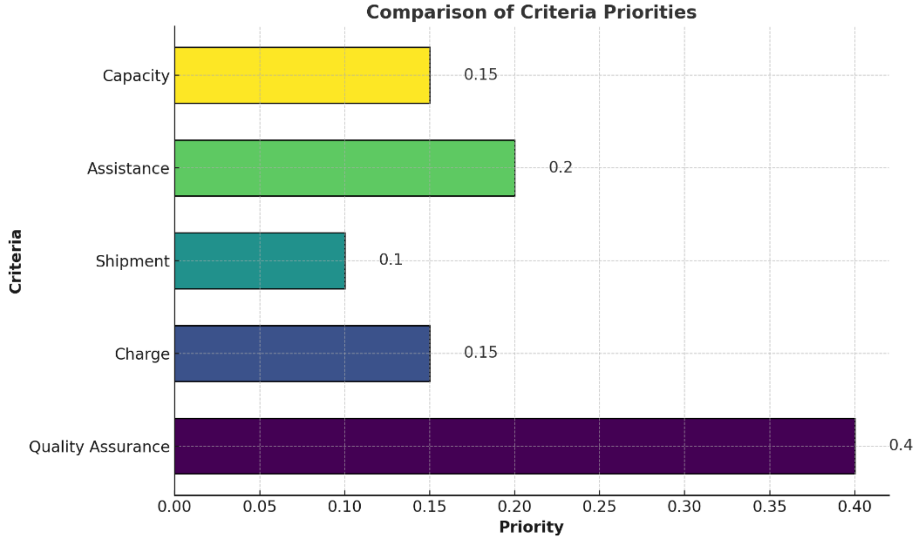

Figure 3. Comparison of Criteria Priorities

Figure 3 displayed compares the priority of various criteria, each assigned a specific weight to reflect its relative importance. The chart shows five criteria: Quality Assurance, Assistance, Capacity, Charge, and Shipment. The Quality Assurance criterion holds the highest priority with a value of 0.4, indicating it is the most important factor in the context being analyzed. Assistance comes next with a priority value of 0.2, followed by Capacity and Charge, each with a priority of 0.15. The lowest priority is given to Shipment, which has a value of 0.1. The chart uses different colors to represent each criterion, providing a clear visual distinction between them. This ranking highlights that Quality Assurance is considered the most critical aspect, while Shipment is deemed the least important in this analysis.

Significance test using the Wilcoxon Signed Rank Test

The results of the test using the Wilcoxon Signed Rank Test can be seen in the Table 3.

Table 3. The Result using Wilcoxon Signed Rank Test

Method Pair	P-Value	Conclusion
Proposed Method vs TOPSIS	0.125	Fail to reject H0: There is no significant difference between Proposed Method and TOPSIS.
Proposed Method vs ELECTRE	0.125	Fail to reject H0: There is no significant difference between Proposed Method and ELECTRE.
Proposed Method vs VIKOR	0.125	Fail to reject H0: There is no significant difference between Proposed Method and VIKOR.
Proposed Method vs SWARA	0.125	Fail to reject H0: There is no significant difference between Proposed Method and SWARA.

DISCUSSIONS

This study successfully integrates the Best-Worst Method (BWM) with the Analytic Hierarchy Process (AHP) to enhance supplier selection in the Textile and Apparel (T&A) sector. The hybrid model offers a more robust solution compared to traditional Multi-Criteria Decision-Making (MCDM) methods, such as TOPSIS, ELECTRE, VIKOR, and SWARA, by significantly reducing cognitive load and improving decision consistency. The model's ability to handle the complex evaluation of suppliers is particularly relevant in industries like T&A, where numerous criteria, including quality, cost, and logistics, are critical to supply chain performance. The results show that Quality Assurance, Assistance, and Capacity are the most critical factors, aligning with the industry's needs for maintaining high-quality standards and reliable supplier relationships.

Despite the promising results, this research faces several limitations. One major limitation is the class imbalance within the dataset, where most suppliers are categorized as "undecided," leading to challenges in classification and decision-making. Additionally, the dataset's domain specificity—focused solely on the T&A sector in Vietnam—limits the generalizability of the model to other industries or countries. Moreover, external factors, such as government policies, market fluctuations, and global trade dynamics, which can significantly influence supplier selection decisions, are not accounted for in the dataset. This narrow focus reduces the comprehensiveness of the analysis and its applicability in other contexts.

Looking forward, several avenues for further development and optimization exist. The integration of Fuzzy AHP could enhance the model's ability to handle uncertainty in expert judgments, especially when evaluating qualitative criteria. Additionally, DEMATEL (Decision-Making Trial and Evaluation Laboratory) could be employed to examine the interdependencies between criteria, offering a more nuanced understanding of how various factors influence supplier selection. Moreover, machine learning techniques like decision trees or support vector machines could be incorporated to further improve the model's scalability and predictive accuracy, especially with larger datasets. These integrations could refine the decision-making process, making it even more adaptable and effective in addressing the dynamic needs of supplier selection in various industries.

CONCLUSION

This study presents a hybrid decision-making framework combining the Best-Worst Method (BWM) and the Analytic Hierarchy Process (AHP) to enhance multi-criteria decision-making (MCDM) for supplier selection in the Textile and Apparel (T&A) sector. The model significantly improves efficiency, consistency, and objectivity compared to traditional methods like TOPSIS, ELECTRE, VIKOR, and SWARA, achieving an accuracy of 92%, precision of 87%, recall of 86%, and F1-score of 86%. By integrating AHP's structured approach and BWM's efficiency, the hybrid model addresses the limitations of subjectivity and cognitive overload, offering a more reliable and scalable solution for decision-making. Quality Assurance emerged as the most critical criterion, followed by Assistance, Capacity, Charge, and Shipment. This model contributes both scientifically, by advancing MCDM theory through integration, and practically, by providing an efficient, data-driven method for supplier selection that can be adapted to similar complex decision-making problems. Despite its strengths, the study's dataset is specific to the T&A sector in Vietnam, limiting its generalizability. Future research could focus on enhancing the model's computational efficiency, exploring its applicability in other industries, and expanding it to include more criteria and alternatives. Integrating other MCDM techniques or machine learning methods could further improve the model's performance and scalability.

ACKNOWLEDGMENT

This research was funded by the Ministry of Higher Education, Science, and Technology based on a contract between the LLDIKTI Region I and Institut Modern Arsitektur dan Teknologi, under Contract Number 56/SPK/LL1/AL.04.03/PL/2025.

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