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*Research article*

# Algorithmic framework for strategic robotics procurement in academia: An integrated optimization approach using GBWM and VIKOR

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**Abstract:** This study addresses a critical challenge in strategic decision-making and resource allocation: The unsystematic procurement of single-arm robotic systems for university curricula. This study introduces a dual-stage computational framework designed to transform qualitative pedagogical requirements into a rigorous mathematical optimization model. The proposed method innovatively synthesizes the group best–worst method (GBWM) with the Visekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) algorithm to establish a stabilized decision-making architecture. The novelty of this approach lies in its ability to resolve the inherent "pedagogical economic paradox" by balancing high-precision technical performance with the stringent budgetary and safety constraints of academic environments, which remain unaddressed in standard industrial models. By leveraging the linear optimization principles of the GBWM, the framework minimizes the maximum absolute deviation in expert consensus, effectively reducing the "cognitive noise" prevalent in subjective procurement. The integration of VIKOR further enhances the model by using a compromise-ranking logic that penalizes individual criterion regret, ensuring that no single academic priority is sacrificed for the overall performance. The results quantified through this methodology reveal that cost (48.4%) and repeatability (22%) are the primary determinants, a prioritization that diverges significantly from industrial benchmarks. This study provides a replicable algorithmic roadmap that empowers academic institutions to optimize resource management, demonstrating the strategic importance of applied mathematics in bridging the gap between engineering management and educational utility.

**Keywords:** educational robotics; GBWM; VIKOR; compromise solution; applied mathematics; algorithmic design and analysis; optimization; MCDM
**Mathematics Subject Classification:** 90B50, 90C29

## 1. Introduction

The widespread integration of robotic systems across diverse sectors, including healthcare [1–3], manufacturing [4–6], logistics [7–9], construction [10–12], and management [13–15], has established a foundational reliance on complex computational and engineering methods.

This paradigm shift mandates the development of a highly proficient workforce, positioning robust robotics education as a strategic imperative for academic institutions [16–18].

Despite the clear recognition of this necessity, a critical operational and methodological challenge persists: The absence of a systematic and mathematically rigorous framework for selecting appropriate robotic platforms for university-level curricula [19–21]. The current selection procedures, which are often informal, rely on subjective expert intuition or inadequate single-criterion metrics, leading to inefficient resource allocation and pedagogically suboptimal results.

The central premise of this study is the deployment of rigorously applied mathematics, specifically multi-criteria decision-making (MCDM) theory, to resolve this complex selection problem. The selection of specialized educational robotics is intrinsically a problem of network optimization and algorithmic complexity, requiring the simultaneous evaluation and balancing of conflicting objectives, such as cost, performance, safety, and educational utility [22].

This study introduces an integrated MCDM framework for the sustainable and strategic selection of single-arm robotic systems in academic environments. Unlike industrial decision processes that prioritize simple performance metrics, the proposed methodology rigorously quantifies and resolves inherent trade-offs within an academic context. This approach leverages a hybrid model that combines the group best-worst method (GBWM) and the Visekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique. GBWM applies the principles of constrained optimization to establish objective criteria weights with demonstrated statistical robustness, whereas VIKOR implements utility theory and distance metrics to derive an optimal compromise solution, collectively providing a decisive application of computational theory and advanced algorithm design to a real-world educational engineering dilemma.

The proposed integrated MCDM approach provides methodological resilience anchored in the GBWM, which uses a linear optimization model to minimize the consistency ratios. This advancement ensures that the criteria weights remain robust even when the expert opinions exhibit high variance, effectively filtering out 'cognitive outliers' that typically compromise the decision quality. Second, the effectiveness of the decision-making procedure is amplified by VIKOR compromise logic. Unlike distance-only models, this framework incorporates an acceptable stability verification phase, ensuring that the final ranking can withstand fluctuations in the criteria's priority. This structural enhancement transforms the selection process from a rigid ranking into a dynamic decision support system capable of providing reliable outcomes in complex, multi-objective academic environments, where budgetary and pedagogical goals are frequently in conflict.

Thus, the primary objective was to create a universally applicable and mathematically defensible framework for adoption by academic leaders. This study provides a clear, data-driven methodology that empowers informed decision-making, thereby contributing to the development of a future workforce capable of addressing the complex challenges of a robotic society. The multifaceted contributions of this study are as follows.

1. We present a focused review of existing MCDM applications in robot selection, with an emphasis on the mathematical structures and limitations of prevailing models in educational contexts.
2. The derivation of a comprehensive set of educationally relevant selection criteria, incorporating expert consensus, serves as the foundational quantitative input for the optimization algorithm.
3. The practical application of the proposed GBWM VIKOR model provides a rigorous demonstration of the algorithm's design and analysis by evaluating and ranking alternative robotic systems.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on robot selection methodologies and the state of educational robotics. Section 3 details the integrated MCDM framework, including the GBWM and VIKOR methodologies. The practical application of the framework, including data extraction, analysis, and a sensitivity analysis, is presented in Section 4. Section 5 discusses the results and implications of this study. Finally, Section 6 summarizes the key findings and outlines the avenues for future research.

## 2. The mathematical and pedagogical contexts of selecting robotics

### *2.1. The educational and diverse role of educational robots*

The global rise in educational robotics (ER) over the past decade has demonstrated the value of this platform as a flexible teaching aid across all academic stages and subjects. It extends from core disciplines, such as mathematics and coding, to creative fields such as art [23–25]. These systems, comprising both physical components and programming, offer experiential learning that builds crucial technical proficiency and essential interpersonal abilities, including collaboration and critical thinking [26,27]. This approach actively improves proficiency and enthusiasm in science, technology, engineering, arts, and mathematics (STEAM) subjects [28–30]. Furthermore, the capacity of these systems to foster an inclusive, tailored, and unbiased classroom setting benefits diverse student bodies [31]. Consequently, determining the optimal teaching robot involves considering the capacity for overall student growth and creating an accessible learning space, rather than simply mechanical specifications [32]. This inherent conflict between technical specifications and pedagogical utility establishes the selection challenge as a multi-criteria optimization problem.

### *2.2. Applications for desired MCDM for robot selection*

Recent developments in computational decision-making have further validated the utility of GBWM and VIKOR in complex engineering environments. For instance, Roshanravan et al. [33] successfully applied the GBWM to modeling mineral potential, whereas Haseli et al. [34] extended the method to spherical fuzzy sets to handle high-uncertainty data. Similarly, Chen et al. [35] demonstrated the robustness of VIKOR for service-oriented resource allocation in healthcare capacity planning. Furthermore, hybrid frameworks that integrate these methods show significant promise. For example, Luo et al. [36] combined the GBWM, CRITIC, and VIKOR for industrial risk assessments, and Zhang et al. [37] used a modified GBWM VIKOR approach for evaluating infrastructure. These contemporary studies confirm that the GBWM VIKOR structure is a cutting-edge approach for resolving multi-objective conflict.

The methodological complexity inherent in balancing technical and pedagogical criteria necessitates the deployment of a mathematically rigorous decision-making framework. The application of MCDM methods constitutes a fundamental application of applied mathematics [38–40] and computational theory, which is designed to solve complex real-world trade-off scenarios [41–43]. Recent advancements in MCDM have led to the development of specialized hybrid models for complex domains. Kousar et al. [44] applied method based on the removal effects of criteria (MEREC) with GBWM for smog mitigation, utilizing objective data variance for weighting, whereas our academic context relies on subjective pedagogical preferences. Kolour et al. [45] integrated fuzzy decision-making trial and evaluation laboratory (DEMATEL) to map causal relationships in supplier selection; however, robotic specifications, such as payload and cost, function as independent trade-offs rather than interlinked causal factors. Furthermore, Anjum et al. [46] used linear diophantine fuzzy Z-numbers to manage high data uncertainty in transportation. In contrast, the primary challenge in robotics procurement is not data's vagueness but stakeholder consensus on deterministic specifications, justifying the use of the GBWM over complex fuzzy or causal modeling extensions.

These studies collectively affirm the utility of complex algorithmic frameworks and optimization principles in resolving procurement challenges in robotics research. However, despite the extensive use of MCDM models, which draw extensively from optimization principles, linear algebra, and utility theory, for selecting industrial and general robot, these established models are rarely directly transferable to the unique constraints of academic environments.

### *2.3. Research gap: lack of a systematic MCDM methodology in higher education*

A systematic evaluation of the existing literature reveals a fundamental misalignment between traditional selection frameworks and the specific requirements of higher education institutions. While Table 1 enumerates various MCDM applications, a critical gap is identified in the transition from industrial efficiency to pedagogy effectiveness.

Existing research on industrial robot selection predominantly prioritizes technical throughput metrics such as operational speed and payload capacity [47,48]. While these parameters are vital for manufacturing, they fail to account for the pedagogical utility required in academic settings. In university laboratories, the primary objective is not reducing the cycle time but rather the transparency of robotic kinematics and safety of student robot interactions.

Strategic procurement in academia necessitates a unique weighting profile that balances ease of programming, curriculum alignment, and long-term economic viability [49,50]. Prior studies often utilize standard weighting techniques that do not effectively capture the high level of subjectivity and cognitive noise present in group decision-making within faculty committees. The absence of a GBWM approach in ER procurement represents a significant methodological oversight, as it leaves the selection processes vulnerable to expert inconsistency.

Most current models focus on identifying a performance leader, which may be unsuitable for educational environments where a single failure in a critical criterion (e.g., software's open-source availability or safety) renders the platform unusable. The literature currently lacks a combined GBWM VIKOR framework specifically designed to identify a compromise solution that optimizes group utility while strictly minimizing individual regret [51].

**Table 1.** Previous studies on robot selection using MCDM conducted between 2019 and 2023.

| Study | Year | Weights calculation | Alternative ranking | Robot application | | | |
|---|---|---|---|---|---|---|---|
| | | | | Industrial | Social | Medical | Educational |
| Mecheri and Christopher [52] | 2019 | | Analytic hierarchy process (AHP) | ✓ | | | |
| Narayanamoorthy et al. [53] | 2019 | Interval-valued intuitionistic hesitant fuzzy sets (IVIHFS) | VIKOR | ✓ | | | |
| Nasrollahi et al. [54] | 2020 | Fuzzy best–worst method (BWM) | PROMETHEE | ✓ | | | |
| Rashid et al. [55] | 2021 | Generalized interval-valued trapezoidal fuzzy weights (GIVTFW) | Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and VIKOR | ✓ | | | |
| Zhao et al. [56] | 2021 | Entropy, criteria importance through intercriteria correlation (CRITIC) | Multi-criteria group decision-making with incomplete preference (MCGDM-IP) | ✓ | | | |
| Bairagi [57,58] | 2022 | Entropy | Technique for additive ranking of alternatives (TARO), TOPSIS | ✓ | | | |
| Kaya et al. [59] | 2022 | IVPFS | DEMATEL and analytic network process (ANP) | | ✓ | | |
| Kang et al. [60] | 2022 | BWM | Multi-attribute utility theory (MAUT) | | | ✓ | |
| Chodha et al. [61] | 2022 | Entropy | TOPSIS | ✓ | | | |
| Garg et al. [62] | 2023 | Step-wise weight assessment ratio analysis (SWARA) | Combined compromise solution (CoCoSo) | ✓ | | | |
| Sampathkumar et al. [63] | 2023 | Fuzzy entropy | Weighted aggregated sum product assessment (WASPAS) | ✓ | | | |
| This study | | GBWM | VIKOR | | | | ✓ |

Without a structured and mathematically grounded selection process, academic institutions risk substantial capital expenditures on systems that lack curricular integration. This study fills this void by introducing a robust algorithmic framework, ensuring that robot selection is a direct reflection of both computational optimization and strategic educational goals.

## 3. An integrated MCDM framework

This study outlines a structured and systematic methodology for the comprehensive evaluation and selection of single-arm robots for university education. The proposed approach integrates two powerful MCDM methods, GBWM and VIKOR, to provide a robust data-driven framework. This dual methodology represents a critical application of computational theory and applied mathematics designed to overcome the limitations of subjective and informal selection processes by providing a transparent and replicable algorithmic roadmap for decision-making. The framework was designed to transform qualitative expert judgment into quantitative and mathematically rigorous inputs for the decision-making model.

The selection of the GBWM for determining the criteria weights is justified by its superior capacity to ensure mathematical consistency over other MCDM techniques. Although newly developed methods such as the full consistency method (FUCOM), level-based weight assessment (LBWA), and defining interrelationships between ranked criteria (DIBR) have emerged to reduce the total number of pairwise comparisons, the GBWM remains more robust for high-stakes academic procurement. The primary advantage of the GBWM lies in its use of two reference vectors (best-to-others and others-to-worst), which provide redundant verification. This dual-comparison mechanism significantly enhances the reliability of the results by minimizing the consistency ratio, a feature that is less prominent in methods such as DIBR or FUCOM, where reduced comparisons may lead to higher sensitivity to initial-ranking errors. However, certain limitations of the GBWM are acknowledged, most notably the increased cognitive load placed on the 17 experts during the pairwise comparison phase. Despite the demand for more extensive data input, the trade-off is justified by the resulting stability of the weight vectors. In the context of selecting robotics for higher education, where technical precision and economic viability are paramount, the rigorous optimization foundation of the GBWM ensures that the final weights reflect a stabilized consensus that is less prone to the subjective biases often found in simpler, fewer-comparison frameworks.

The VIKOR method is uniquely suited to the ER selection problem because it focuses on compromise solutions derived from utility and distance metrics. While other distance-based frameworks such as technique for order of preference by similarity to ideal solution (TOPSIS), measurement of alternatives and ranking according to compromise solution (MARCOS), Multi-attributive border approximation area comparison (MABAC), and Additive Ratio Technique with advanced subjective information (ARTASI) offer valuable ranking capabilities, VIKOR is distinguished by its specific focus on the pedagogical economic paradox through a compromise-ranking logic. Because a single “perfect” robot does not exist, the proposed method identifies the optimal alternative based on its proximity to the ideal solution while addressing inherent multi-objective conflicts. VIKOR utilizes two core measures: Group utility (S) and individual regret (R). The inclusion of R ensures that the ranking does not merely select an alternative that performs well on average (group utility), which is a common limitation in methods such as TOPSIS, but actively penalizes poor performance on any single critical criterion. For educational procurement, where failure in a single area, such as safety or ease of use, can render a system unusable, minimizing individual regret is a vital mathematically enforced constraint.

The combined use of the GBWM and VIKOR creates a powerful synergy. The highly consistent and mathematically optimized weights generated by the GBWM provide high-precision inputs for the VIKOR ranking algorithm. This integration ensures that the final decision is not an arbitrary compromise but a computationally sound, prioritized list of alternatives, enhancing the overall accuracy and credibility of the results. The overall research process was logically organized into three distinct phases to ensure a thorough and rigorous analysis (Figure 1).

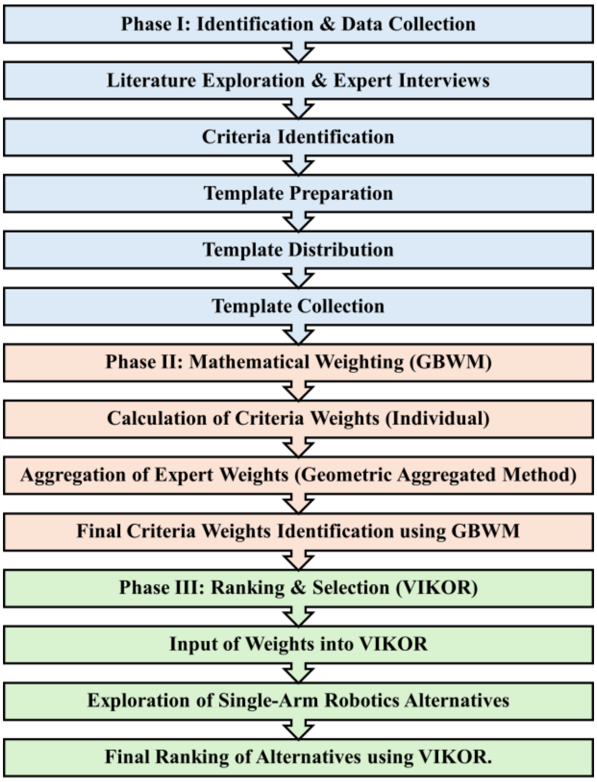


**Figure 1.** Flowchart of the systematic three-phase methodology for evaluating single-arm robotics.

*3.1. Criteria identification and expert engagement*

This initial phase established a foundation for the entire evaluation process. The study begins with an exhaustive literature review of academic and industrial publications to identify the initial set of criteria for assessing educational robots. This step ensured that the framework was built on a strong theoretical and practical basis, providing a comprehensive pool of potential variables for the multi-criteria decision model. The selection criteria presented in Table 2 represent the translation of educational needs into quantifiable technical metrics.

**Table 2.** Systematic rationale for the inclusion of the selection criteria.

| Criteria | Technical indicator | Rationale for inclusion |
|---|---|---|
| Structural and design features (C1) | Degrees of freedom (DoF) (C11) | It is essential to align the robot's mechanical complexity with advanced robotics curricula and kinematic modeling. |
| | Reachability (C12) | It is necessary to ensure that the robot can operate within the physical constraints of university laboratories and perform various experimental tasks. |
| | Weight (C13) | The system must be designed to be easily relocated and safely handled by students, ensuring safety and portability. |
| Performance and precision (C2) | Payload (C21) | It is necessary to determine the robot's ability to support various educational end-effectors and sensor integration projects. |
| | Repeatability (C22) | It is critical to provide students with high-precision data to validate control algorithms and theoretical dynamic simulations. |
| | Speed (C23) | In addition, the efficiency of classroom laboratory sessions and the study of real-time robotic motion control were evaluated. |
| Cost (3) | Cost | The long-term economic viability and feasibility of acquiring multiple units for student access were evaluated. |

Following the literature review, a diverse panel of domain specialists and academic researchers was recruited. In-depth interviews were conducted to gather qualitative insights, validate the criteria identified in the literature, and identify additional criteria with practical significance for an academic context. This rigorous process is essential for transforming broad educational objectives into specific, measurable, and mathematically tractable criteria suitable for the quantitative weighting phase. The validated and finalized set of criteria was then used to design a structured evaluation template for the GBWM. This design ensured a consistent and comprehensive data collection process for all the experts. The completed templates were meticulously verified for completeness and accuracy before proceeding to the next phase of the study. Systematic engagement with experts ensures that the initial qualitative input is reliable, thus laying the groundwork for the robust optimization required by the GBWM algorithm in the subsequent stages.

### *3.2. Criteria weighing and aggregation with the GBWM*

GBWM, a prominent MCDM technique introduced by Rezaei [64], was used in this phase to determine the relative importance of each criterion. The GBWM is advantageous because it minimizes inconsistencies in pairwise comparisons, leading to highly reliable and consistent criteria weights. The steps for implementing the GBWM are as follows:

Step #1: Establish the full set of criteria, $C = \{C_1, C_2, \dots C_n\}$, identified in Phase 1.

Step #2: Identify the best and worst criteria. Each expert identifies the most important (best) criterion, $A_B \epsilon\ C$, and the least important (worst) criterion, $A_W \epsilon\ C$, from the set.

Step #3: Conduct best-to-others comparisons. The best criterion, $A_B$, is compared against all other criteria using a numerical scale from 1 to 9 (see Table 3). This results in a vector, $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$, where $a_{Bj}$ represents the preference for B over criterion j.

Step #4: Conduct others-to-worst comparisons. All criteria are compared against the worst criterion, $A_W$, using the same numerical scale. This generates a vector, $A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T$, where a $a_{jw}$ quantifies the preference for criterion j over W.

**Table 3.** Verbal and numerical scales used for pairwise comparisons in GBWM.

| Verbal judgment | Numeric value |
|---|---|
| Extremely important | 9 |
| Very high importance | 8 |
| Substantially more important | 7 |
| Considerably more important | 6 |
| Significantly more important | 5 |
| Perceptibly more important | 4 |
| Slightly more important | 3 |
| Minor importance | 2 |
| Equally important | 1 |

Step #5: Formulate an optimization model. The optimal weights for each criterion are represented as $(w_1^*, w_2^*, \ldots, w_n^*)$. For every criterion pair j and W, the relationship $\frac{W_j}{W_w} = a_{jW}$ is expected. To fulfill these conditions across all values of j, a solution is sought by minimizing the maximum absolute discrepancies between the expected and actual ratios, specifically considering $\left| \frac{W_B}{W_j} - a_{Bj} \right|$ and $\left| \frac{W_j}{W_w} - a_{jw} \right|$. Factoring in the constraints of non-negativity for all weights and their summation to unity leads to the following mathematical formulation:

$$min\, max_{\,j} \{ \left| \frac{W_B}{W_j} - a_{Bj} \right|, \left| \frac{W_j}{W_w} - a_{jw} \right| \tag{1}$$

s.t

$$\sum_j W_j = 1$$

Where $W\_j \geqslant 0$, for all $j$.

Step #6: Aggregate the expert weights. The individual criterion weights from each expert were aggregated using a geometric mean approach, which is a standard method for combining ratio scale data. This ensures that the collective judgment of the expert panel is accurately represented and preserves the relative proportions of each expert's assessment. The aggregated weight, $W_j$, is calculated using Equation 2:

$$W_j = \left(\prod_{i=1}^{N} w_{ij}\right)^{\frac{1}{N}}. \tag{2}$$

*3.3. Alternative evaluation and ranking with the VIKOR method*

In the final phase, the aggregated criterion weights are applied to rank the alternative robotic systems. The VIKOR method, first proposed by Opricovic [65], was used for this purpose in this study. This method identifies a compromise solution according to its proximity to the ideal alternative. The steps are as follows.

Step #1: Normalize the decision matrix. The raw data for all the alternatives were normalized to ensure comparability. The normalization formula is

$$f_{ij}(x) = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, \dots, m \; ; j = 1, \dots, n \tag{3}$$

Step #2: Determine the best and worst values for each criterion. The positive ideal $f_i^*$ and negative ideal $f_i^-$ solutions are identified for each criterion. If the criterion is beneficial (positive), then

$$f_j^* = Max_i f_{ij} \; , \; f_j^- = Min_i f_{ij} \; ; \; j = 1,2, \dots, n \tag{4}$$

If the criterion is non-beneficial (negative), then

$$f_j^* = Min_i f_{ij} \; , \; f_j^- = Max_i f_{ij} \; ; \; j = 1,2, \dots, n \tag{5}$$

The positive ideal solution ($f^*$) and the negative ideal solution ($f^-$) for all criteria can then be expressed as

$$f^* = \{f_1^*, f_2^*, f_3^*, \dots, f_n^*\} \tag{6}$$

$$f^- = \{f_1^-, f_2^-, f_3^-, \dots, f_n^-\} \tag{7}$$

Step #3: Compute the group utility and individual regret. The values for group utility $S_i$ and individual regret $R_i$ are calculated for each alternative using the following formulas:

$$S_i = \sum_{j=1}^{n} w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \tag{8}$$

$$R_i = Max_j \left[ w_j \frac{\left(f_j^* - f_{ij}\right)}{\left(f_j^* - f_j^-\right)} \right] \tag{9}$$

Step #4: Calculate the VIKOR index. The VIKOR index $Q_i$ is computed for each alternative. This index represents the final compromise ranking value.

$$Q_i = \gamma \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - \gamma) \frac{(R_i - R^*)}{(R^- - R^*)} \tag{10}$$

where

$$S^* = Min_i\{S_i\};$$

$$S^- = Max_i\{S_i\};$$

$$R^* = Min_i\{R_i\};$$

$$R^- = Max_i\{R_i\}$$

and $\gamma$ represents the weight of the "majority criteria" (or maximum group utility), commonly set at 0.5.

Step #5: Rank the alternatives. The alternatives were ranked according to their Q values. The alternative with the lowest Q-value is ranked first. The final ranking was determined using a set of criteria to ensure that the chosen solution was robust.

To determine a final compromise solution, the alternative ($A^{(1)}$) holding the top rank according to the Q measure (i.e., the alternative possessing the lowest Q value) must satisfy two specific conditions.

- Criterion 1: Sufficient advantage. This condition requires that the difference between the Q values of the second- and first-ranked alternatives be at least 1/(m−1), where m represents the total number of alternatives in the set. Symbolically, $Q(A^{(2)}) - Q(A^{(1)}) \geq DQ.$ Here, ($A^{(1)}$) denotes the leading alternative in the Q-based ranking, and ($A^{(2)}$) signifies the alternative immediately following it.
- Criterion 2: Robustness in ranking. The top-ranked alternative, ($A^{(1)}$), must also demonstrate superior ranking when evaluated by the S measure, the R measure, or both. If one or both of these criteria are not met, a collection of compromise alternatives is proposed.
- Option 1: Insufficient Advantage. If Criterion 1 is not satisfied, the compromise set encompasses the alternatives $A^{(1)}, A^{(2)}, \ldots, A^{(M)}$. $A^{(M)}$ is selected on the basis of the highest Q value among alternatives considered to be in proximity in the ranking.
- Option 2: Decision instability occurs if only Criterion 2 is not satisfied, the compromise set is limited to the top two alternatives, $A^{(1)}$ and $A^{(2)}$.
- Option 3: Full compliance. If both Criterion 1 and Criterion 2 are fully satisfied, the alternative with the absolute minimum Q is definitively chosen as the singular best solution.

This integrated methodology provides a comprehensive, systematic, and transparent approach for selecting single-arm educational robots. By combining the strengths of the GBWM for precise weighting and VIKOR for robust ranking, this framework offers a powerful tool for academic institutions to make informed decisions that align with their pedagogical and economic goals.

## 4. Analysis and results

This section comprehensively presents and interprets the findings derived from the integrated MCDM framework tailored for the strategic selection of single-arm robots in university education. It details the hierarchical organization of the selection criteria, quantifies their relative significance through expert weighting, and elucidates the systematic evaluation and ranking of various robotic alternatives. The culmination of this analysis provides actionable recommendations for educational institutions seeking to optimize their robotics curriculum and resource allocation.

*4.1. Hierarchical structure of the selection criteria and expert validation*

This evaluation is based on a meticulously structured hierarchy of criteria for selecting single-arm robots (Figure 2).

This framework systematically organizes the assessment into three primary criteria: Structural and design features, cost, and performance precision. Each of these overarching categories encompasses several sub-criteria, all of which play a pivotal role in the holistic evaluation process and reflect crucial considerations for both industrial engineering principles and effective academic management.

Structural and design features were used to examine the fundamental physical attributes and operational capabilities of the robotic system.

For example, the degrees of freedom (DoFs) quantify the dexterity of a robot, directly affecting its versatility in demonstrating advanced movements and complex tasks that are crucial for educational scenarios.

Reachability (mm) defines the operational workspace of the robot, allowing a broader spectrum of experimental setups and interactions in a laboratory environment.

Weight (kg) pertains to the mass of the robot, which influences portability, ease of installation, and potential reconfiguration within dynamic university lab settings.

The payload (kg) denotes the maximum mass that the end effector can manipulate, thereby expanding the scope for diverse experiments involving heavier objects or specialized tooling.

Cost encompasses the economic implications of acquisitions and ongoing operations. Given the typical budgetary constraints of academic institutions, this criterion is substantially important in resource management decisions. Performance precision focuses on the functional accuracy and efficiency of robots.

Repeatability (mm) measures the robot's ability to consistently return to a precise position, which is paramount for experiments that require high accuracy and reliable data collection.

Speed (m/s, maximum tool center point (TCP)) indicates the maximum velocity of the robot's tool center point, facilitating the demonstration of dynamic movements and time-sensitive tasks that are essential for comprehensive student understanding.

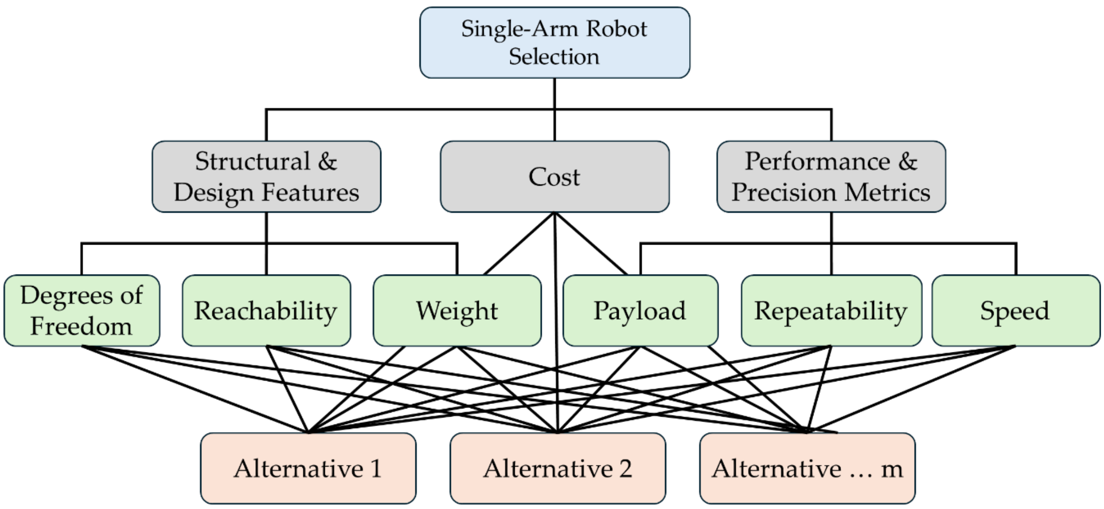


**Figure 2.** Hierarchy of single-arm robot-selection criteria.

To ensure the robustness and objectivity of the criteria and their subsequent weighting, an evaluation questionnaire was rigorously administered to a panel of 17 experts. This panel comprised both seasoned academic professionals and industry practitioners, each possessing a minimum of five years of demonstrable experience in robotics applications within either the academic or industrial domains, as detailed in Table 4.

**Table 4.** Profiles of the experts recruited for the study.

| Expert # | Qualification | Field | Experience (years) |
|---|---|---|---|
| 1 | Ph.D. | Academic | 8 |
| 2 | | | 7 |
| 3 | | | 9 |
| 4 | | | 8 |
| 5 | | | 7 |
| 6 | | | 8 |
| 7 | | | 9 |
| 8 | | | 6 |
| 9 | | | 6 |
| 10 | | | 5 |
| 11 | | | 5 |
| 12 | | Industry | 5 |
| 13 | | | 7 |
| 14 | | | 6 |
| 15 | | | 7 |
| 16 | | | 7 |
| 17 | | | 5 |

This stringent selection protocol guarantees the incorporation of diverse, informed, and highly pertinent perspectives that are essential for the integrity of analytical phases. Even with a modest number of experts (17), this approach aligns with standard practices for MCDM that rely on expert assessments.

A large number of participants is not the key determinant of methodological soundness in this type of study. Validity is established by carefully selecting experts with extensive practical experience [66,67] and a deep theoretical grasp of the topic [68–70]. The indispensable contributions and insights of these individuals are fundamental to this study.

### 4.2. Expert-weighted criteria, prioritizing educational needs

The relative importance of each criterion was quantitatively determined by aggregating expert judgments using the GBWM. The raw assessments from the panel of experts, which formed the basis for these calculated weights, are presented in Tables 5–10. The calculated weights for the main criteria and their respective sub-criteria are listed in Table 11. These weights provide a clear, data-driven measure of the significance of the criteria in the robot selection process.

**Table 5.** Experts' best-to-other main criteria evaluation.

| | | Main criteria | | |
|---|---|---|---|---|
| Expert # | Best-to-others | Structural and design features (C1) | Performance and precision metrics (C2) | Cost (C3) |
| 1 | C3 | 5 | 7 | 1 |
| 2 | C2 | 7 | 1 | 9 |
| 3 | C2 | 5 | 1 | 8 |
| 4 | C3 | 6 | 6 | 1 |
| 5 | C3 | 5 | 7 | 1 |
| 6 | C2 | 6 | 1 | 9 |
| 7 | C3 | 4 | 6 | 1 |
| 8 | C2 | 6 | 1 | 8 |
| 9 | C3 | 6 | 8 | 1 |
| 10 | C3 | 5 | 4 | 1 |
| 11 | C3 | 5 | 4 | 1 |
| 12 | C3 | 4 | 6 | 1 |
| 13 | C2 | 4 | 1 | 7 |
| 14 | C3 | 7 | 5 | 1 |
| 15 | C2 | 8 | 1 | 9 |
| 16 | C3 | 6 | 8 | 1 |
| 17 | C3 | 6 | 5 | 1 |

**Table 6.** Experts' best-to-other structural and design features criterion evaluation.

| | | Structural and design features criterion | | |
|---|---|---|---|---|
| Expert# | Best-to-others | DoFs (C11) | Reachability (C12) | Weight (C13) |
| 1 | C11 | 1 | 5 | 7 |
| 2 | C11 | 1 | 2 | 4 |
| 3 | C11 | 1 | 5 | 7 |
| 4 | C11 | 1 | 9 | 9 |
| 5 | C11 | 1 | 2 | 7 |
| 6 | C11 | 1 | 6 | 8 |
| 7 | C11 | 1 | 1 | 6 |
| 8 | C11 | 1 | 1 | 3 |
| 9 | C11 | 1 | 6 | 8 |
| 10 | C11 | 1 | 8 | 8 |
| 11 | C11 | 1 | 8 | 9 |
| 12 | C11 | 1 | 4 | 6 |
| 13 | C11 | 1 | 4 | 6 |
| 14 | C11 | 1 | 9 | 9 |
| 15 | C11 | 1 | 3 | 6 |
| 16 | C11 | 1 | 3 | 8 |
| 17 | C11 | 1 | 9 | 8 |

**Table 7.** Experts' best-to-other performance and precision criterion evaluation.

| Performance and precision metrics | | | | |
|---|---|---|---|---|
| Expert# | Best criterion | Payload (C21) | Repeatability (C22) | Speed (C23) |
| 1 | C22 | 8 | 1 | 3 |
| 2 | C22 | 7 | 1 | 3 |
| 3 | C22 | 4 | 1 | 6 |
| 4 | C22 | 4 | 1 | 3 |
| 5 | C22 | 2 | 1 | 7 |
| 6 | C22 | 5 | 1 | 7 |
| 7 | C22 | 1 | 1 | 6 |
| 8 | C22 | 6 | 1 | 2 |
| 9 | C22 | 9 | 1 | 4 |
| 10 | C22 | 2 | 1 | 2 |
| 11 | C22 | 5 | 1 | 3 |
| 12 | C22 | 7 | 1 | 2 |
| 13 | C22 | 3 | 1 | 5 |
| 14 | C22 | 5 | 1 | 4 |
| 15 | C22 | 8 | 1 | 4 |
| 16 | C22 | 3 | 1 | 8 |
| 17 | C22 | 4 | 1 | 4 |

**Table 8.** Experts' others-to-worst evaluations of the main criteria.

| Main criteria | | | | |
|---|---|---|---|---|
| Expert # | Others-to-worst | Structural and design features (C1) | Performance and precision metrics (C2) | Cost (C3) |
| 1 | C1 | 1 | 7 | 7 |
| 2 | C3 | 7 | 7 | 1 |
| 3 | C3 | 2 | 6 | 1 |
| 4 | C1 | 1 | 1 | 6 |
| 5 | C2 | 6 | 1 | 7 |
| 6 | C3 | 3 | 7 | 1 |
| 7 | C2 | 5 | 1 | 6 |
| 8 | C3 | 6 | 6 | 1 |
| 9 | C1 | 1 | 8 | 8 |
| 10 | C1 | 1 | 1 | 5 |
| 11 | C1 | 1 | 1 | 6 |
| 12 | C1 | 1 | 6 | 6 |
| 13 | C3 | 1 | 5 | 1 |
| 14 | C1 | 1 | 1 | 7 |
| 15 | C3 | 8 | 8 | 1 |
| 16 | C2 | 7 | 1 | 8 |
| 17 | C1 | 1 | 1 | 6 |

**Table 9.** Experts' others-to-worst evaluations of the structural and design features criterion.

| Structural and design features criterion | | | | |
|---|---|---|---|---|
| Expert# | Others-to-worst | DoFs (C11) | Reachability (C12) | Weight (C13) |
| 1 | C13 | 5 | 7 | 1 |
| 2 | C13 | 4 | 4 | 1 |
| 3 | C13 | 7 | 3 | 1 |
| 4 | C13 | 9 | 9 | 1 |
| 5 | C13 | 7 | 7 | 1 |
| 6 | C13 | 8 | 4 | 1 |
| 7 | C13 | 6 | 6 | 1 |
| 8 | C13 | 3 | 3 | 1 |
| 9 | C13 | 6 | 8 | 1 |
| 10 | C13 | 8 | 1 | 1 |
| 11 | C13 | 8 | 1 | 1 |
| 12 | C13 | 4 | 6 | 1 |
| 13 | C13 | 6 | 2 | 1 |
| 14 | C13 | 9 | 2 | 1 |
| 15 | C13 | 5 | 5 | 1 |
| 16 | C13 | 8 | 8 | 1 |
| 17 | C13 | 9 | 1 | 1 |

**Table 10.** Experts' others-to-worst evaluations of the performance and precision criterion.

| Performance and precision criterion | | | | |
|---|---|---|---|---|
| Expert# | Others-to-worst | Payload (C21) | Repeatability (C22) | Speed (C23) |
| 1 | C21 | 1 | 5 | 4 |
| 2 | C21 | 1 | 7 | 3 |
| 3 | C23 | 1 | 6 | 1 |
| 4 | C23 | 3 | 3 | 1 |
| 5 | C23 | 3 | 7 | 1 |
| 6 | C23 | 1 | 7 | 1 |
| 7 | C23 | 2 | 6 | 1 |
| 8 | C21 | 1 | 6 | 2 |
| 9 | C21 | 1 | 6 | 5 |
| 10 | C23 | 2 | 2 | 1 |
| 11 | C23 | 4 | 3 | 1 |
| 12 | C21 | 1 | 4 | 3 |
| 13 | C23 | 1 | 5 | 1 |
| 14 | C23 | 4 | 4 | 1 |
| 15 | C21 | 1 | 8 | 4 |
| 16 | C23 | 4 | 8 | 1 |
| 17 | C23 | 3 | 4 | 1 |

Table 11 presents the distribution of these weights among the primary criteria for the assessment. The results in Table 11 visually reinforce that repeatability and cost have emerged as the most critical factors as seen in Figure 3, demonstrating the emphasis of the academic community on functional accuracy and economic viability for long-term operational efficiency.

**Table 11.** Single-arm robots' criteria weights.

| Criteria/sub-criteria | Type | Main criteria | Sub-criteria | Global weight |
|---|---|---|---|---|
| Structural and design features | | 18.6% | | |
| DoFs | Maximization | | 71% | 13.2% |
| Reachability | Maximization | | 20.0% | 3.7% |
| Weight | Minimization | | 9.2% | 1.7% |
| Performance and precision metrics | | 33% | | |
| Payload | Maximization | | 16.5% | 5.4% |
| Repeatability | Minimization | | 67.0% | 22.0% |
| Speed | Maximization | | 16.5% | 5.4% |
| Cost | Minimization | 48.4% | | 48.4% |

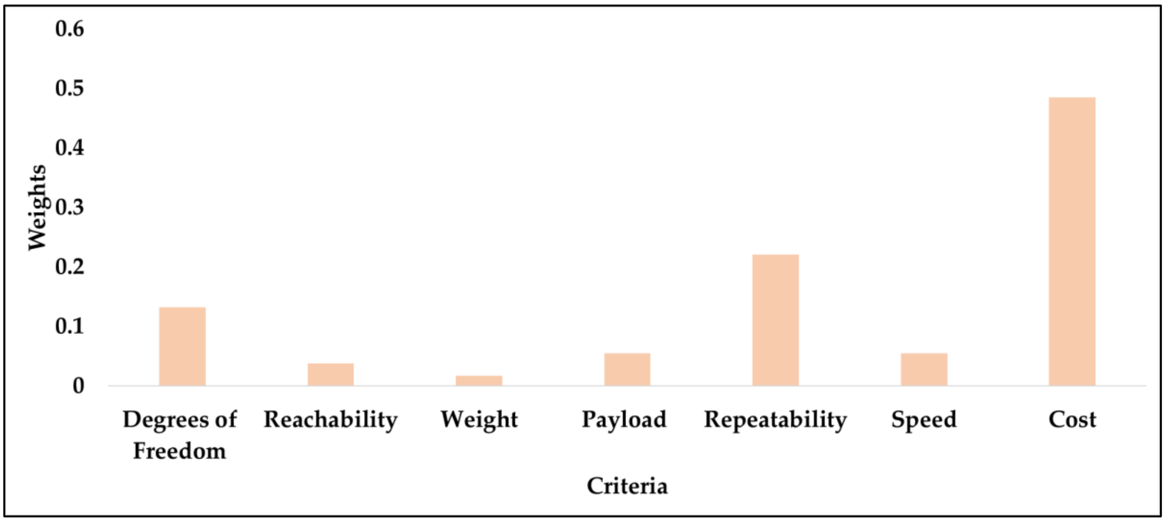


**Figure 3.** Distribution of aggregated criteria weights from the expert panel's assessments.

*4.3. Evaluation and optimal selection*

The precisely determined criteria weights serve as the cornerstone for evaluating and ranking various single-arm robotics. The initial data for each alternative, encompassing their performance values across the defined criteria, are detailed in the decision matrix presented in Table 12. This matrix forms the fundamental input for the subsequent MCDM.

The quantitative data for the 48 single-arm robotic alternatives were systematically extracted [71–73], utilizing information sourced from an official [74–76], centralized robotics repository [77,78]. These sources provide standardized technical specifications and market pricing for both educational and industrial platforms, thereby ensuring a consistent baseline for comparison.

**Table 12.** Decision matrix.

| Alt. | DoFs | Reachability | Weight | Payload | Repeatability | Speed | Cost |
|---|---|---|---|---|---|---|---|
| 1 | 6 | 717 | 25 | 7 | 0.01 | 11 | 25000 |
| 2 | 6 | 1249 | 40 | 10 | 0.04 | 2 | 35000 |
| 3 | 6 | 2655 | 1090 | 165 | 0.05 | 3 | 65000 |
| 4 | 6 | 1853 | 250 | 25 | 0.023 | 3 | 40000 |
| 5 | 6 | 280 | 17 | 0.5 | 0.02 | 4 | 22000 |
| 6 | 6 | 580 | 21 | 4 | 0.01 | 2.2 | 24000 |
| 7 | 6 | 1400 | 78.5 | 7 | 0.03 | 6.2 | 28000 |
| 8 | 6 | 1650 | 272 | 20 | 0.04 | 6.6 | 38000 |
| 9 | 6 | 2050 | 425 | 60 | 0.06 | 6.5 | 50000 |
| 10 | 7 | 559 | 38 | 0.5 | 0.02 | 1.5 | 40000 |
| 11 | 6 | 927 | 37 | 7 | 0.01 | 4.5 | 20000 |
| 12 | 6 | 1200 | 48 | 10 | 0.1 | 1 | 30000 |
| 13 | 6 | 1730 | 250 | 25 | 0.02 | 4 | 35000 |
| 14 | 6 | 1440 | 150 | 12 | 0.02 | 5 | 32000 |
| 15 | 6 | 1440 | 150 | 12 | 0.02 | 4 | 25000 |
| 16 | 6 | 901 | 55 | 6 | 0.02 | 6.5 | 22000 |
| 17 | 6 | 1101 | 56 | 10 | 0.03 | 8.7 | 30000 |
| 18 | 7 | 820 | 30 | 14 | 0.1 | 2 | 65000 |
| 19 | 6 | 2080 | 540 | 30 | 0.04 | 8 | 45000 |
| 20 | 6 | 2500 | 1049 | 120 | 0.06 | 2.5 | 70000 |
| 21 | 6 | 500 | 11.2 | 3 | 0.03 | 1 | 33000 |
| 22 | 6 | 850 | 20.6 | 5 | 0.03 | 1 | 37000 |
| 23 | 6 | 1300 | 33.5 | 12.5 | 0.05 | 1 | 49500 |
| 24 | 6 | 900 | 33.1 | 16 | 0.05 | 1 | 55000 |
| 25 | 4 | 432 | 14 | 1 | 0.01 | 4 | 13000 |
| 26 | 6 | 450 | 19 | 1 | 0.02 | 3 | 20000 |
| 27 | 6 | 920 | 40 | 3 | 0.1 | 0.8 | 15000 |
| 28 | 6 | 903 | 37 | 5 | 0.03 | 9.3 | 24000 |
| 29 | 6 | 2200 | 740 | 100 | 0.2 | 5 | 55000 |
| 30 | 4 | 760 | 210 | 2 | 0.05 | 1.5 | 40000 |
| 31 | 6 | 649 | 41 | 4 | 0.02 | 6 | 23000 |
| 32 | 6 | 908 | 67 | 7 | 0.02 | 6 | 26000 |
| 33 | 6 | 432 | 15 | 2 | 0.02 | 3.9 | 18000 |
| 34 | 6 | 605 | 35 | 4 | 0.02 | 9.39 | 25000 |
| 35 | 6 | 920 | 52 | 3.7 | 0.02 | 6.9 | 30000 |
| 36 | 6 | 1200 | 117 | 12 | 0.025 | 7.6 | 20000 |
| 37 | 4 | 600 | 20 | 6 | 0.02 | 7.5 | 16000 |
| 38 | 6 | 809 | 34 | 5 | 0.03 | 6 | 28000 |
| 39 | 6 | 900 | 27 | 6 | 0.05 | 0.25 | 38000 |
| 40 | 6 | 900 | 39 | 5 | 0.05 | 1 | 30000 |
| 41 | 6 | 700 | 22 | 6 | 0.05 | 1.1 | 27000 |

*Continued on next page*

| Alt. | DoFs | Reachability | Weight | Payload | Repeatability | Speed | Cost |
|---|---|---|---|---|---|---|---|
| 42 | 6 | 724 | 30 | 7 | 0.02 | 5 | 20000 |
| 43 | 6 | 1350 | 36 | 10 | 0.05 | 1.5 | 22000 |
| 44 | 6 | 954 | 22 | 7 | 0.02 | 1.5 | 18000 |
| 45 | 6 | 1412 | 120 | 12 | 0.05 | 4 | 25000 |
| 46 | 6 | 700 | 22 | 4 | 0.05 | 1.1 | 26000 |
| 47 | 7 | 850 | 18 | 3 | 0.03 | 2.5 | 25000 |
| 48 | 6 | 1200 | 33 | 12 | 0.03 | 1.5 | 24000 |

To ensure fair and unbiased comparisons across criteria that inherently possess disparate units and scales, the raw decision matrix data underwent rigorous normalization. The resulting normalized decision matrix, as shown in Table 13, represents these transformed values. This crucial normalization step prevents criteria with wider numerical ranges from disproportionately influencing the final evaluation outcomes.

**Table 13.** Normalized decision matrix.

| Alt. | DoFs | Reachability | Weight | Payload | Repeatability | Speed | Cost |
|---|---|---|---|---|---|---|---|
| 1 | 0.145 | 0.085 | 0.013 | 0.029 | 0.029 | 0.327 | 0.105 |
| 2 | 0.145 | 0.148 | 0.021 | 0.041 | 0.115 | 0.059 | 0.147 |
| 3 | 0.145 | 0.315 | 0.569 | 0.673 | 0.143 | 0.089 | 0.272 |
| 4 | 0.145 | 0.22 | 0.13 | 0.102 | 0.066 | 0.089 | 0.168 |
| 5 | 0.145 | 0.033 | 0.009 | 0.002 | 0.057 | 0.119 | 0.092 |
| 6 | 0.145 | 0.069 | 0.011 | 0.016 | 0.029 | 0.065 | 0.101 |
| 7 | 0.145 | 0.166 | 0.041 | 0.029 | 0.086 | 0.184 | 0.117 |
| 8 | 0.145 | 0.196 | 0.142 | 0.082 | 0.115 | 0.196 | 0.159 |
| 9 | 0.145 | 0.243 | 0.222 | 0.245 | 0.172 | 0.193 | 0.209 |
| 10 | 0.169 | 0.066 | 0.02 | 0.002 | 0.057 | 0.045 | 0.168 |
| 11 | 0.145 | 0.11 | 0.019 | 0.029 | 0.029 | 0.134 | 0.084 |
| 12 | 0.145 | 0.142 | 0.025 | 0.041 | 0.287 | 0.03 | 0.126 |
| 13 | 0.145 | 0.205 | 0.13 | 0.102 | 0.057 | 0.119 | 0.147 |
| 14 | 0.145 | 0.171 | 0.078 | 0.049 | 0.057 | 0.148 | 0.134 |
| 15 | 0.145 | 0.171 | 0.078 | 0.049 | 0.057 | 0.119 | 0.105 |
| 16 | 0.145 | 0.107 | 0.029 | 0.024 | 0.057 | 0.193 | 0.092 |
| 17 | 0.145 | 0.131 | 0.029 | 0.041 | 0.086 | 0.258 | 0.126 |
| 18 | 0.169 | 0.097 | 0.016 | 0.057 | 0.287 | 0.059 | 0.272 |
| 19 | 0.145 | 0.247 | 0.282 | 0.122 | 0.115 | 0.237 | 0.189 |
| 20 | 0.145 | 0.297 | 0.547 | 0.489 | 0.172 | 0.074 | 0.293 |
| 21 | 0.145 | 0.059 | 0.006 | 0.012 | 0.086 | 0.03 | 0.138 |
| 22 | 0.145 | 0.101 | 0.011 | 0.02 | 0.086 | 0.03 | 0.155 |
| 23 | 0.145 | 0.154 | 0.017 | 0.051 | 0.143 | 0.03 | 0.207 |
| 24 | 0.145 | 0.107 | 0.017 | 0.065 | 0.143 | 0.03 | 0.23 |
| 25 | 0.097 | 0.051 | 0.007 | 0.004 | 0.029 | 0.119 | 0.054 |

*Continued on next page*

| Alt. | DoFs | Reachability | Weight | Payload | Repeatability | Speed | Cost |
|---|---|---|---|---|---|---|---|
| 26 | 0.145 | 0.053 | 0.01 | 0.004 | 0.057 | 0.089 | 0.084 |
| 27 | 0.145 | 0.109 | 0.021 | 0.012 | 0.287 | 0.024 | 0.063 |
| 28 | 0.145 | 0.107 | 0.019 | 0.02 | 0.086 | 0.276 | 0.101 |
| 29 | 0.145 | 0.261 | 0.386 | 0.408 | 0.573 | 0.148 | 0.23 |
| 30 | 0.097 | 0.09 | 0.11 | 0.008 | 0.143 | 0.045 | 0.168 |
| 31 | 0.145 | 0.077 | 0.021 | 0.016 | 0.057 | 0.178 | 0.096 |
| 32 | 0.145 | 0.108 | 0.035 | 0.029 | 0.057 | 0.178 | 0.109 |
| 33 | 0.145 | 0.051 | 0.008 | 0.008 | 0.057 | 0.116 | 0.075 |
| 34 | 0.145 | 0.072 | 0.018 | 0.016 | 0.057 | 0.279 | 0.105 |
| 35 | 0.145 | 0.109 | 0.027 | 0.015 | 0.057 | 0.205 | 0.126 |
| 36 | 0.145 | 0.142 | 0.061 | 0.049 | 0.072 | 0.226 | 0.084 |
| 37 | 0.097 | 0.071 | 0.01 | 0.024 | 0.057 | 0.223 | 0.067 |
| 38 | 0.145 | 0.096 | 0.018 | 0.02 | 0.086 | 0.178 | 0.117 |
| 39 | 0.145 | 0.107 | 0.014 | 0.024 | 0.143 | 0.007 | 0.159 |
| 40 | 0.145 | 0.107 | 0.02 | 0.02 | 0.143 | 0.03 | 0.126 |
| 41 | 0.145 | 0.083 | 0.011 | 0.024 | 0.143 | 0.033 | 0.113 |
| 42 | 0.145 | 0.086 | 0.016 | 0.029 | 0.057 | 0.148 | 0.084 |
| 43 | 0.145 | 0.16 | 0.019 | 0.041 | 0.143 | 0.045 | 0.092 |
| 44 | 0.145 | 0.113 | 0.011 | 0.029 | 0.057 | 0.045 | 0.075 |
| 45 | 0.145 | 0.168 | 0.063 | 0.049 | 0.143 | 0.119 | 0.105 |
| 46 | 0.145 | 0.083 | 0.011 | 0.016 | 0.143 | 0.033 | 0.109 |
| 47 | 0.169 | 0.101 | 0.009 | 0.012 | 0.086 | 0.074 | 0.105 |
| 48 | 0.145 | 0.142 | 0.017 | 0.049 | 0.086 | 0.045 | 0.101 |

Subsequent to the normalization process, the decision matrix was subjected to calculations to determine the best $f^*$ and worst $f^-$ values for each criterion. These values were integrated into the VIKOR method. Subsequently, the S and R values for each alternative were calculated. The S value represents the utility measure (distance to the ideal solution), and the R value represents the regret measure (maximum regret of the opponent). Finally, the Q values, which combine the S and R values, were computed to provide a comprehensive ranking. The calculated S, R, and Q values for each alternative, along with their derived rankings, are presented in Table 14.

**Table 14.** Final ranking alternatives.

| Alt. | R value | Rank in R | S value | Rank in S | Q value | Rank in Q |
|---|---|---|---|---|---|---|
| 1 | 0.102 | 7 | 0.228 | 6 | 0.074 | 8 |
| 2 | 0.187 | 16 | 0.384 | 35 | 0.335 | 34 |
| 3 | 0.442 | 24 | 0.589 | 45 | 0.845 | 45 |
| 4 | 0.229 | 19 | 0.39 | 36 | 0.392 | 38 |
| 5 | 0.076 | 4 | 0.258 | 14 | 0.076 | 9 |
| 6 | 0.093 | 6 | 0.267 | 16 | 0.105 | 14 |
| 7 | 0.127 | 11 | 0.291 | 21 | 0.17 | 23 |
| 8 | 0.212 | 18 | 0.38 | 34 | 0.361 | 35 |

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| Alt. | R value | Rank in R | S value | Rank in S | Q value | Rank in Q |
|---|---|---|---|---|---|---|
| 9 | 0.314 | 22 | 0.489 | 41 | 0.593 | 42 |
| 10 | 0.229 | 19 | 0.376 | 33 | 0.376 | 37 |
| 11 | 0.059 | 3 | 0.215 | 2 | 0.012 | 2 |
| 12 | 0.144 | 13 | 0.417 | 38 | 0.321 | 33 |
| 13 | 0.187 | 16 | 0.341 | 29 | 0.291 | 31 |
| 14 | 0.161 | 14 | 0.318 | 27 | 0.237 | 29 |
| 15 | 0.102 | 7 | 0.264 | 15 | 0.112 | 16 |
| 16 | 0.076 | 4 | 0.234 | 7 | 0.052 | 7 |
| 17 | 0.144 | 13 | 0.299 | 24 | 0.197 | 26 |
| 18 | 0.442 | 24 | 0.669 | 47 | 0.929 | 47 |
| 19 | 0.272 | 20 | 0.427 | 39 | 0.479 | 40 |
| 20 | 0.484 | 25 | 0.662 | 46 | 0.97 | 48 |
| 21 | 0.17 | 15 | 0.374 | 32 | 0.305 | 32 |
| 22 | 0.204 | 17 | 0.402 | 37 | 0.374 | 36 |
| 23 | 0.31 | 21 | 0.522 | 42 | 0.622 | 43 |
| 24 | 0.357 | 23 | 0.573 | 44 | 0.73 | 44 |
| 25 | 0.131 | 12 | 0.255 | 13 | 0.136 | 19 |
| 26 | 0.059 | 3 | 0.243 | 8 | 0.041 | 6 |
| 27 | 0.104 | 8 | 0.297 | 22 | 0.149 | 21 |
| 28 | 0.093 | 6 | 0.249 | 9 | 0.087 | 11 |
| 29 | 0.357 | 23 | 0.69 | 48 | 0.853 | 46 |
| 30 | 0.229 | 19 | 0.54 | 43 | 0.549 | 41 |
| 31 | 0.085 | 5 | 0.25 | 11 | 0.078 | 10 |
| 32 | 0.11 | 9 | 0.271 | 18 | 0.129 | 18 |
| 33 | 0.054 | 2 | 0.222 | 3 | 0.012 | 3 |
| 34 | 0.102 | 7 | 0.25 | 12 | 0.098 | 13 |
| 35 | 0.144 | 13 | 0.301 | 25 | 0.2 | 27 |
| 36 | 0.059 | 3 | 0.212 | 1 | 0.009 | 1 |
| 37 | 0.131 | 12 | 0.27 | 17 | 0.152 | 22 |
| 38 | 0.127 | 11 | 0.301 | 26 | 0.18 | 24 |
| 39 | 0.212 | 18 | 0.436 | 40 | 0.42 | 39 |
| 40 | 0.144 | 13 | 0.365 | 31 | 0.267 | 30 |
| 41 | 0.119 | 10 | 0.341 | 30 | 0.213 | 28 |
| 42 | 0.059 | 3 | 0.227 | 5 | 0.024 | 5 |
| 43 | 0.076 | 4 | 0.286 | 20 | 0.105 | 15 |
| 44 | 0.052 | 1 | 0.224 | 4 | 0.012 | 4 |
| 45 | 0.102 | 7 | 0.298 | 23 | 0.148 | 20 |
| 46 | 0.11 | 9 | 0.334 | 28 | 0.195 | 25 |
| 47 | 0.102 | 7 | 0.249 | 10 | 0.097 | 12 |
| 48 | 0.093 | 6 | 0.281 | 19 | 0.12 | 17 |

According to the robust compromise solution identified using the VIKOR method, the following alternatives emerged as the final optimal selections for single-arm robotic systems suitable for university educational purposes: Alternatives 36, 11, 33, 44, and 42. This set of recommendations offers academic institutions a rigorously evaluated, data-driven portfolio of options, facilitating informed procurement decisions that effectively align with pedagogical objectives, foster experiential learning, and ensure long-term value in industrial engineering and management programs.

### *4.4. Sensitivity analysis*

This subsection presents a rigorous sensitivity analysis to validate the consistency of the findings and ensure methodological resilience. The primary importance of this analysis lies in verifying that the identified ranking remains stable under varying MCDM assessment methods. By performing a comparative assessment via the TOPSIS and PROMETHEE II methodologies, the framework demonstrates that the VIKOR compromise solution is not a mathematical artifact but a robust decision. The stability of these results across different algorithmic logics significantly strengthens the methodology, providing institutional leaders with a high degree of confidence in the final procurement recommendations.

Table 15 presents a detailed comparison of the alternative rankings derived using the VIKOR, PROMETHEE II, and TOPSIS methodologies. This comparative analysis demonstrates the structural integrity of the proposed model by illustrating the convergence of the results across different mathematical frameworks.

**Table 15.** Comparative ranking results across the individual MCDM methods.

| Alt. | PROMETHEE II | | TOPSIS | | VIKOR | |
|---|---|---|---|---|---|---|
| | Score | Rank | Score | Rank | Q value | Rank |
| 1 | 0.366 | 10 | 0.778 | 10 | 0.074 | 8 |
| 2 | −0.238 | 34 | 0.669 | 32 | 0.335 | 34 |
| 3 | −0.507 | 43 | 0.483 | 45 | 0.845 | 45 |
| 4 | −0.204 | 32 | 0.663 | 34 | 0.392 | 38 |
| 5 | 0.326 | 12 | 0.774 | 12 | 0.076 | 9 |
| 6 | 0.343 | 11 | 0.771 | 13 | 0.105 | 14 |
| 7 | 0.013 | 25 | 0.738 | 20 | 0.17 | 23 |
| 8 | −0.222 | 33 | 0.656 | 35 | 0.361 | 35 |
| 9 | −0.463 | 41 | 0.538 | 43 | 0.593 | 42 |
| 10 | −0.165 | 30 | 0.655 | 36 | 0.376 | 37 |
| 11 | 0.577 | 1 | 0.798 | 3 | 0.012 | 2 |
| 12 | −0.306 | 39 | 0.574 | 41 | 0.321 | 33 |
| 13 | −0.006 | 26 | 0.706 | 28 | 0.291 | 31 |
| 14 | 0.038 | 22 | 0.723 | 26 | 0.237 | 29 |
| 15 | 0.274 | 14 | 0.769 | 14 | 0.112 | 16 |
| 16 | 0.410 | 8 | 0.784 | 8 | 0.052 | 7 |
| 17 | −0.028 | 27 | 0.727 | 24 | 0.197 | 26 |
| 18 | −0.519 | 44 | 0.343 | 47 | 0.929 | 47 |
| 19 | −0.294 | 38 | 0.606 | 40 | 0.479 | 40 |
| 20 | −0.603 | 47 | 0.434 | 46 | 0.97 | 48 |

*Continued on next page*

| Alt. | PROMETHEE II | | TOPSIS | | VIKOR | |
|---|---|---|---|---|---|---|
| | Score | Rank | Score | Rank | Q value | Rank |
| 21 | −0.259 | 35 | 0.692 | 30 | 0.305 | 32 |
| 22 | −0.285 | 37 | 0.665 | 33 | 0.374 | 36 |
| 23 | −0.474 | 42 | 0.545 | 42 | 0.622 | 43 |
| 24 | −0.542 | 45 | 0.509 | 44 | 0.73 | 44 |
| 25 | 0.504 | 3 | 0.806 | 1 | 0.136 | 19 |
| 26 | 0.394 | 9 | 0.782 | 9 | 0.041 | 6 |
| 27 | 0.173 | 20 | 0.649 | 37 | 0.149 | 21 |
| 28 | 0.217 | 16 | 0.763 | 16 | 0.087 | 11 |
| 29 | −0.547 | 46 | 0.212 | 48 | 0.853 | 46 |
| 30 | −0.642 | 48 | 0.607 | 39 | 0.549 | 41 |
| 31 | 0.324 | 13 | 0.775 | 11 | 0.078 | 10 |
| 32 | 0.179 | 19 | 0.761 | 17 | 0.129 | 18 |
| 33 | 0.465 | 5 | 0.792 | 6 | 0.012 | 3 |
| 34 | 0.233 | 15 | 0.767 | 15 | 0.098 | 13 |
| 35 | 0.038 | 23 | 0.734 | 23 | 0.2 | 27 |
| 36 | 0.453 | 6 | 0.795 | 4 | 0.009 | 1 |
| 37 | 0.452 | 7 | 0.803 | 2 | 0.152 | 22 |
| 38 | −0.034 | 28 | 0.735 | 22 | 0.18 | 24 |
| 39 | −0.430 | 40 | 0.625 | 38 | 0.42 | 39 |
| 40 | −0.273 | 36 | 0.682 | 31 | 0.267 | 30 |
| 41 | −0.166 | 31 | 0.702 | 29 | 0.213 | 28 |
| 42 | 0.477 | 4 | 0.791 | 7 | 0.024 | 5 |
| 43 | 0.164 | 21 | 0.735 | 21 | 0.105 | 15 |
| 44 | 0.522 | 2 | 0.793 | 5 | 0.012 | 4 |
| 45 | 0.034 | 24 | 0.724 | 25 | 0.148 | 20 |
| 46 | −0.153 | 29 | 0.707 | 27 | 0.195 | 25 |
| 47 | 0.185 | 18 | 0.748 | 19 | 0.097 | 12 |
| 48 | 0.201 | 17 | 0.758 | 18 | 0.12 | 17 |

The comparative analysis presented in Table 15 and the associated line chart in Figure 4 reveal a high degree of convergence among the PROMETHEE II, TOPSIS, and VIKOR ranking outcomes. The top-performing alternatives, specifically Alternatives 11, 36, and 44, consistently occupy the highest ranks across all three divergent mathematical frameworks. While VIKOR identifies Alternative 36 as the primary compromise solution, TOPSIS and PROMETHEE II provide secondary validation by ranking it within the top tier. Such stability in the upper-rank distribution confirms that the selection of optimal robotic systems is not dependent on a specific algorithmic logic but is a robust result of the stabilized criterion weights.

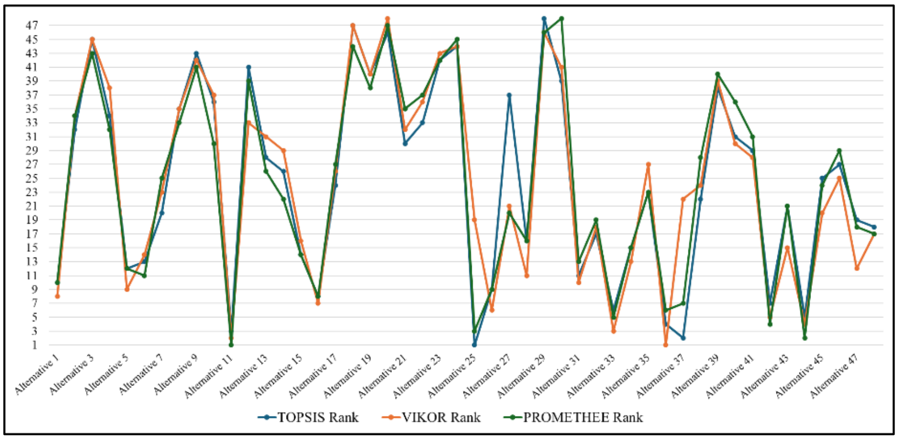


**Figure 4.** Comparative ranking results of robotic alternatives using VIKOR, TOPSIS, and PROMETHEE II.

The structural integrity of the methodology is further evidenced by the consistent tracking of the three ranking lines across 48 alternatives. Although minor fluctuations exist owing to the differing mathematical foundations, where TOPSIS prioritizes the geometric distance from ideal points and PROMETHEE II relies on net preference flows, the overall trend remains synchronized. This synchronization effectively mitigates the risk of methodological bias, ensuring that the final procurement recommendations are resilient. By successfully passing this sensitivity test, the proposed GBWM VIKOR framework proves its reliability as a decision-support tool capable of providing consistent results even when subjected to varying multi-criteria assessment logics.

## 5. Strategic insights for optimized robotics education

The strategic selection of single-arm robotic systems for universities' educational purposes represents a critical endeavor that directly addresses a complex problem within the broader scope of industrial engineering and management. This study leveraged a sophisticated integrated MCDM approach, uniquely combining the GBWM for precise criteria weighting with the VIKOR method for robust ranking of alternatives. This integrated framework offers a transparent and robust mechanism for navigating the inherent complexities of such procurement decisions, particularly where a multitude of conflicting criteria necessitate a compromise solution that balances technical performance with pedagogical and economic realities.

### *5.1. Prioritization of the criteria: reflecting academic imperatives*

The application of the GBWM yielded a hierarchical structure of criteria weights, as quantitatively presented in Table 11 and visually represented in Figure 3. A detailed analysis of these weights provides crucial insights into the priorities that guide the selection of single-arm robots in an academic context, underscoring the interplay between industrial engineering principles and educational management.

Cost (48.4%) emerged as the most dominant criterion, reflecting the pronounced budgetary constraints faced by academic institutions. Unlike industrial settings, where substantial initial investments might be justified by enhanced production capabilities or rapid returns on investment, universities often operate under stringent financial frameworks. This significant weighting of costs highlights its role as a primary determinant of resource allocation, demanding an optimized approach to procurement that maximizes educational value within fiscal limitations. This finding emphasizes the critical management implications of financial prudence for developing educational infrastructure.

Repeatability (22%) was the most critical subcriterion within the performance precision category. For pedagogical objectives, consistent and precise execution of robotic movement is paramount. High repeatability enables students to reliably replicate experiments, observe consistent outcomes, and develop a profound understanding of control algorithms and robotic kinematics, free from confounding variables introduced by inconsistent robot behavior. This strong prioritization of repeatability over factors such as speed directly underscores the academic emphasis on quality control in learning experiences and the reproducibility of experimental results, which are fundamental to engineering education.

DoFs (13.2%), while holding a comparatively high local weight within its main category, exhibited a lower global influence than cost and repeatability. This indicates a nuanced understanding: a sufficient number of DoFs (e.g., six DoFs, typical for industrial-style arms) is indispensable for demonstrating versatility and complex movements. However, additional DoFs beyond a practical threshold may introduce unwarranted complexity and increase costs without a commensurate increase in pedagogical benefits, especially given budgetary limitations.

The payload (5.4%) and speed (5.4%) received relatively low global weights. While these sub-criteria are paramount in industrial applications, where heavy object manipulation or rapid cycle times are essential for operational efficiency, they are generally of moderate importance for educational demonstrations and student projects. Extreme values in these areas often correlate with inflated costs or increased safety complexities for novice users, making them less suitable as primary educational tools.

This weighting profile is in distinct contrast to the established industrial selection frameworks. For instance, previous studies by Narayanamoorthy et al. [53] and Rashid et al. [55] on industrial robot selection consistently identified velocity and load capacity as the top-tier requirements necessary to maximize manufacturing throughput. The divergence of our results confirms that academic procurement operates on a distinct pedagogical economic value curve, where the primary metric of success is not units per hour, but rather reliability per dollar. While industrial models punish low speed as a bottleneck, the academic model finds that moderate speed is often preferable to ensure students' safety and easier visual tracking of the kinematic movements.

Reachability (3.7%) and weight (1.7%) were the least critical factors in this study. The typical range for reachability, which defines the operational workspace of a robot, is generally adequate for most laboratory setups. Similarly, the overall weight of the robot, while impacting portability and ease of setup, was deemed to have minimal influence compared with its performance and cost implications, suggesting that these are secondary considerations in the broader procurement strategy.

### *5.2. Compromise solutions: enhancing decision flexibility*

A key advantage of using the VIKOR method, which is particularly pertinent in the educational context, is its capacity to identify a compromise solution rather than simply a single, top-ranked alternative. In complex decision-making scenarios with inherently conflicting criteria, such as balancing upfront costs against long-term performance and pedagogical utility, relying solely on a single "best" option might lead to suboptimal choices that fail to adequately reconcile all considerations. The robust framework of the VIKOR method provides a set of alternatives that are demonstrably close to the ideal solution and stable within the decision-making process. This implies that the practical differences between these top alternatives are often negligible, thus offering valuable procurement flexibility. This multi-solution approach directly contributes to effective management decision-making by providing a strategic portfolio of choices that maintain optimal outcomes while allowing for practical considerations, such as vendor availability, after-sales support, or specific local integration requirements.

On the basis of the compromise solution criteria specified within the VIKOR methodology, the following five alternatives were identified as optimal single-arm robotic systems for university educational purposes: Alternatives 11, 33, 36, 42, and 44. Despite exhibiting minor variations in their individual group utility (S) and individual regret (R) values, these alternatives demonstrated negligible differences in their final Q (compromise) values, thereby satisfying the rigorous conditions for a valid compromise set. The detailed characteristics extracted from the initial data for operational clarity are presented in Table 16.

From a practical management perspective, this set of compromise solutions offers a defensive procurement strategy for university administrators to consider. Frequently, educational purchasing is driven by the 'lowest bid' rule or, conversely, by the 'prestige purchasing' of overqualified industrial equipment. The identification of these specific compromise alternatives allows laboratory managers to justify capital expenditures to university boards by demonstrating that the selected equipment optimizes the total educational value rather than simply minimizing cost or maximizing theoretical specifications. This shift empowers institutions to standardize the equipment that supports curriculum's consistency across different semesters and instructors.

These specific robotic systems collectively represent pragmatic and academically sound investments. They were selected because of their balanced performance, particularly in adhering to high-priority cost and repeatability criteria, while simultaneously offering sufficient DOFs for a comprehensive educational experience.

**Table 16.** Optimal selection of single-arm robots for educational applications.

| Alt. | DoFs | Reachability | Weight | Payload | Repeatability | Speed | Cost in USD |
|---|---|---|---|---|---|---|---|
| 11 | 6 | 927 | 37 | 7 | ±0.010 | 4.5 | ≈20,000 |
| 33 | 6 | 432 | 15 | 2 | ±0.020 | 3.9 | ≈18,000 |
| 36 | 6 | 1200 | 117 | 12 | ±0.025 | 7.6 | ≈20,000 |
| 42 | 6 | 724 | 30 | 7 | ±0.020 | 5 | ≈20,000 |
| 44 | 6 | 954 | 22 | 7 | ±0.020 | 1.5 | ≈18,000 |

The inherent ability of the VIKOR method to identify this refined set of functionally equivalent optimal alternatives provides institutions with essential flexibility in procurement, enabling them to consider practical logistical factors without compromising the overall quality or pedagogical effectiveness of the selected robotic system for advanced learning and research purposes.

## 6. Conclusions

This study rigorously addresses the critical challenge of systematically selecting single-arm robotic systems for university curricula, bridging the gap between qualitative pedagogical needs and quantitative procurement methods. By integrating the GBWM and VIKOR, this study provides a mathematically robust framework that aligns with the principles of algorithmic design and resource optimization. The primary contribution of this study is the successful application of a linear optimization model to aggregate the preferences of 17 experts, ensuring a stabilized weighting process that minimizes cognitive inconsistencies. A significant finding of this research is the prioritization of cost (48.4%) and repeatability (22%) as the dominant selection criteria. This weighting profile reveals a strategic divergence from industrial benchmarks, highlighting the unique pedagogical and financial constraints that necessitate a tailored mathematical approach to academic institutional management.

Subsequently, the VIKOR method was strategically used to evaluate and rank a comprehensive set of single-arm robotic alternatives on the basis of rigorously weighted criteria. VIKOR's strength, which is grounded in utility theory and distance minimization, lies in its capacity to identify a compromise solution, defined as a set of optimal and functionally equivalent choices, rather than a single best alternative. This feature is particularly advantageous in complex decision environments, where conflicting criteria necessitate flexibility in procurement without compromising educational utility. The robust ranking process culminated in the identification of alternatives 11, 33, 36, 42, and 44 as the most suitable single-arm robotic systems, providing academic institutions with practical, data-driven options.

The proposed framework enables universities to move beyond subjective and informal selection processes, facilitating data-driven procurement decisions that optimize resource allocation and enhance pedagogical outcomes. This study empirically identifies and validates the key criteria driving the selection of educational robots, providing invaluable insights for robot manufacturers and educational policymakers.

Despite its substantial contributions, this study has certain limitations that offer promising avenues for future research. One primary constraint pertains to the descriptive depth of the expert panel profiles. While the 17 participants possessed verified PhD qualifications and a minimum of five years of relevant experience, a more granular breakdown of their specific sub-specializations and professional designations was not exhaustive. This documentation limitation may influence the assessment of the nuanced alignment between individual domain expertise and specific weighting tendencies within the GBWM model.

Furthermore, extending the framework to larger and more geographically diverse expert panels could refine the criteria weights and enhance global applicability. Extending the alternative set to include emerging open-source robotic platforms may provide a more exhaustive and comprehensive comparative assessment. Finally, adapting this hybrid MCDM framework for the selection of other types of ER systems, such as mobile robots or humanoid platforms, represents another fruitful direction for future investigation, broadening the applicability of this rigorous methodology across the entire spectrum of educational robotics and solidifying the role of applied mathematics at the forefront of optimizing industrial and educational management processes.

## Author contributions

All authors have equally contributed to this study.

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## Conflict of interest

The authors declare no conflict of interest.

## Use of Generative–AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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