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Interval Valued Fermatean Neutrosophic for Analysis Risk Management of Practical Teaching Quality in University Art and Design Programs

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Abstract
The quality of practical teaching in university art and design programs is a crucial determinant of students' creative and professional development. However, various risks challenge the effectiveness of these programs, ranging from outdated curricula to inadequate resources and inconsistent evaluation methods. This paper explores a comprehensive risk management framework to enhance the quality of practical teaching in art and design education. It examines key factors such as faculty expertise, infrastructure, student engagement, and industry collaboration. Through a structured risk analysis, universities can develop proactive strategies to mitigate challenges, ensuring that students receive high-quality, relevant, and practical training. The study uses multi-criteria decision-making (MCDM) methodology with two methods. One method named Entropy method to compute the criteria weights, and another method named MAIRCA to rank the alternatives. These methods are used under the interval valued Fermatean neutrosophic sets to overcome uncertainty and vague information. An application is shown to show the validation of the proposed approach.

Keywords: Risk Management; Teaching Quality; University Art and Design Programs; MCDM Approach; Interval Valued Fermatean Neutrosophic.

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1. Introduction

Practical teaching is the cornerstone of education in art and design disciplines. It acts as the critical link between theoretical knowledge and hands-on creative exploration, allowing students to develop essential skills through studio work, workshops, and project-based experiences. These activities not only shape students' artistic identities but also prepare them for the expectations and demands of creative industries. However, delivering high-quality practical education presents multiple challenges that must be addressed to ensure that learning outcomes are both meaningful and professionally relevant.

One of the most significant concerns facing academic institutions is the rapidly evolving nature of the creative sector. Design tools, market trends, and client expectations continue to shift, requiring educational programs to be equally dynamic. Without continuous curriculum updates, investment in modern facilities, and strong alignment with industry needs, students risk graduating with skills that are no longer applicable in the professional world. In the absence of a structured risk management framework, universities may find it difficult to maintain the quality of their teaching or to effectively prepare graduates for competitive job markets [1][2].

A number of specific issues hinder the effectiveness of practical education. Among them is the shortage of faculty with up-to-date industry experience, which limits students' exposure to real-world processes and standards. Many academic programs still rely on outdated instructional content or teaching methods, which do not reflect current industry tools such as digital modeling, user experience design, or sustainable material practices. Furthermore, challenges like limited access to specialized equipment, insufficient funding, and a lack of standardization in assessment make it difficult to maintain consistency and fairness in evaluating creative work [3][4].

The quality of infrastructure plays a central role in shaping students' learning experiences. Studios, digital labs, and specialized workspaces must be equipped with contemporary tools and technologies that reflect actual industry conditions. Unfortunately, many institutions struggle to upgrade or even maintain these resources due to budget constraints or slow administrative processes. Moreover, the integration of emerging technologies such as virtual reality, AI-driven tools, and digital fabrication methods presents new opportunities for learning, but also introduces fresh risks related to access, training, and technological adaptability [3].

Another longstanding challenge lies in the evaluation of student performance. Unlike more objective fields, practical disciplines often lack standardized assessment methods. Creativity, originality, and conceptual depth are inherently difficult to grade, and traditional numeric or letter-based systems do not always capture the quality of a student's work. This leads to subjectivity, inconsistent grading, and frustration for both students and instructors. To address this, institutions must adopt modern assessment frameworks that incorporate industry benchmarks, peer reviews, and project-based evaluations to ensure fair, transparent, and constructive feedback [5][6].

Strong collaboration between universities and industry professionals is essential to keep curricula aligned with real-world practices. Exposure to professional environments allows students to understand project workflows, client interaction, and collaborative design thinking. However, many universities lack structured engagement programs, resulting in limited student access to internships, mentorship, or live projects. Creating sustainable partnerships with design firms, studios, and creative agencies is essential for bridging this gap and preparing students for real-world expectations [4].

Equally important is the need to enhance student engagement. Traditional, lecture-based instruction often fails to capture students' full creative potential in practical subjects. Instead, interactive strategies such as problem-based learning, team projects, and real-world simulation tasks can foster deeper engagement and build confidence. Cultivating a learning environment that supports experimentation, peer feedback, and risk-taking encourages students to explore new techniques and refine their artistic vision [7][8].

Given the complexity of these challenges, a structured and forward-looking risk management framework is essential. This includes regular curriculum evaluation, investment in faculty training, infrastructure development, and implementation of standardized yet flexible assessment models. Furthermore, universities should establish feedback systems involving students, instructors, and industry representatives to detect weaknesses early and ensure continuous improvement. When implemented effectively, such a model ensures that art and design education remain responsive, competitive, and capable of producing industry-ready graduates.

To model these risks and evaluate them accurately, it is important to adopt a decision-making approach that accommodates uncertainty, subjectivity, and incomplete information, all of which are common in educational evaluations. Traditional methods often fall short in capturing the nuanced perspectives of experts or the overlapping nature of creative criteria. To address this, the study draws on neutrosophic set theory, first introduced by Smarandache, which expands fuzzy logic by adding an indeterminacy component, allowing a more realistic representation of vague or conflicting expert opinions [9][10].

Building on this foundation, interval-valued neutrosophic sets, introduced by Wang, allow evaluations to include a range of possible values rather than fixed estimates, improving flexibility and accuracy in uncertain environments. More recently, Fermatean neutrosophic sets, described by Jansi, have further extended these concepts by offering even greater capacity to model expert hesitation, partial belief, and conflicting data [11][12]. These theoretical tools form the basis of the current study's methodology, which combines interval-valued Fermatean neutrosophic environments with entropy-based weighting and the MAIRCA method to produce a comprehensive and reliable risk analysis model tailored to the realities of practical teaching in art and design education.

1.1 Objectives and Contributions

The primary objective of this study is to develop a structured and uncertainty-aware decision-making framework to evaluate the risks affecting the quality of practical teaching in art and design education. While various educational studies have highlighted the challenges of delivering hands-on learning, few have approached the issue from a formal risk assessment perspective using advanced multi-criteria decision-making tools. This research addresses that gap by proposing a model that combines interval-valued Fermatean neutrosophic sets (IVFNS), entropy weighting, and the MAIRCA method to assess multiple risk scenarios based on expert evaluations.

Specifically, the study aims to:

1. Identify the critical dimensions influencing the quality of practical teaching in art and design programs.
2. Model and assess real-world risk scenarios that may hinder effective learning outcomes.
3. Incorporate expert hesitation, uncertainty, and subjectivity using interval-valued Fermatean neutrosophic logic.
4. Apply an objective weighting approach using Shannon's entropy method to determine the importance of each criterion.
5. Rank risk scenarios using the MAIRCA method to provide clear guidance for academic decision-makers.

The key contributions of this study can be summarized as follows:

1. It introduces a comprehensive risk-based evaluation model tailored to the unique characteristics of art and design education.
2. It is one of the few studies to apply IVFNS logic in combination with entropy and MAIRCA for assessing educational risks.
3. The model captures subjective expert knowledge more effectively than traditional MCDM approaches.
4. The findings provide prioritization of risk scenarios, enabling institutions to allocate resources and policy interventions more strategically.
5. The study contributes a replicable methodology that can be adapted by other faculties or institutions facing similar challenges in practice-based disciplines.

2. Literature Review

The development and delivery of high-quality practical teaching in art and design programs have been widely discussed across educational literature, with particular attention given to curriculum design, pedagogical practices, student learning environments, and performance evaluation methods. While many studies have highlighted the importance of hands-on learning in creative disciplines, there remains a lack of consensus on how to systematically assess and manage the risks associated with these environments, especially in contexts characterized by uncertainty, limited resources, and qualitative judgments.

Recent literature has acknowledged that the effectiveness of practical teaching is strongly influenced by a range of interdependent factors. For instance, Gungor and Polat (2018) examined the relationship between studio conditions and student satisfaction, concluding that well-maintained, well-equipped workspaces significantly enhance both creativity and motivation in design education [1]. Their work emphasizes the infrastructural dimension but does not propose a systematic method to assess its risk level or how it interacts with other dimensions such as faculty quality or curriculum structure.

The role of academic staff in shaping the quality of hands-on education has also been widely acknowledged. Cohen et al. (2014) discussed the importance of instructor experience and pedagogical competence in art and design teaching, noting that reliance on traditional or overly theoretical approaches often leads to a disconnect between what students learn and the realities of professional design work [2]. However, while their findings stress the need for pedagogical reform, they do not address how faculty-related risks can be quantitatively evaluated or compared with other institutional challenges.

Another important strand in the literature focuses on the assessment of student work in creative contexts. Jabben et al. (2015) explored the inconsistencies that arise when grading subjective outputs such as visual projects, proposing more structured rubrics and assessment frameworks to mitigate bias [3]. Yet, despite the value of these suggestions, the authors stop short of integrating their approach into a broader risk management framework that considers institutional factors and resource availability.

The dynamic nature of the design industry has further highlighted the urgency for educational programs to evolve. Halecki et al. (2023) emphasized the need for frequent curriculum revisions that incorporate digital technologies, sustainability, and interdisciplinary collaboration [4]. Their study provides direction on what to include in future curricula but does not suggest how to evaluate the risks associated with outdated course content or lack of alignment with industry trends.

Across these studies, a recurring limitation is the lack of a unified, risk-focused framework that captures the complexity of practical teaching in design disciplines. While individual factors—such as curriculum relevance, faculty qualification, or infrastructure quality—are often explored in isolation, few models exist that can assess their combined effect or prioritize intervention areas.

To overcome this challenge, researchers have increasingly looked at multi-criteria decision-making (MCDM) methods, which allow for structured evaluation of complex problems involving multiple conflicting criteria. Techniques such as AHP and TOPSIS have been applied in educational settings, including in curriculum evaluation and institutional planning. However, traditional MCDM methods often assume clear, numeric data inputs and do not perform well when information is vague, incomplete, or uncertain conditions that are common in art and design education [5].

In response to these limitations, neutrosophic logic has emerged as a powerful tool for managing uncertainty in decision-making processes. Introduced by Smarandache, neutrosophic sets expand upon classical fuzzy logic by incorporating an indeterminacy component, allowing evaluators to express hesitation or incomplete knowledge [6]. This makes the approach particularly well-suited for contexts such as education, where expert judgments are often based on subjective experiences rather than measurable data.

Wang (2010) further developed interval-valued neutrosophic sets, which allow experts to express their evaluations as value ranges rather than single points, enhancing the flexibility and realism of the model [7]. Building on this, Jansi and colleagues introduced Fermatean neutrosophic sets, which provide even greater capacity for modeling expert uncertainty, particularly in multi-criteria environments where overlapping priorities and subjective evaluations are the norm [8].

Applications of these mathematical models in education are still relatively recent but growing. For instance, Wang et al. (2019) used interval neutrosophic sets in evaluating software quality in academic environments, demonstrating the potential of these models in capturing complex expert input [9]. Similarly, Jansi and his co-authors applied Fermatean neutrosophic techniques to measure teaching effectiveness in higher education, highlighting the value of these methods in decision-making processes involving ambiguity and judgment-based criteria [10].

Despite these advances, few studies have applied such approaches to evaluate risk in practical teaching environments, especially within the context of creative disciplines like art and design. This gap is particularly striking given the inherently uncertain and subjective nature of these fields. The absence of a comprehensive model capable of integrating various risks ranging from infrastructure deficits to misalignment with industry—continues to limit institutions' ability to plan effectively and respond to evolving educational demands.

The current study addresses this gap by proposing a hybrid model that combines interval-valued Fermatean neutrosophic sets with entropy-based weighting and the MAIRCA method. This integrated framework enables a nuanced evaluation of risk scenarios, considering both expert hesitation and the varying importance of different teaching dimensions. It allows academic institutions to not only identify critical weaknesses in their practical teaching environments but also to prioritize interventions based on structured, data-informed insights.

In conclusion, the reviewed literature demonstrates a strong foundation in the analysis of individual components of practical teaching. However, it lacks an integrated, quantitative, and uncertainty-aware framework for risk evaluation. By adopting a novel neutrosophic-MCDM approach, this research builds on previous work and contributes to a new methodology capable of supporting strategic decision-making in art and design education.

3. Theoretical Background

In evaluating complex educational environments such as those found in art and design institutions, traditional models of assessment often fall short. These models typically rely on fixed metrics, deterministic logic, or rigid evaluation frameworks that are poorly equipped to handle the ambiguity, subjectivity, and dynamic interplay of factors involved in practical teaching. As such, a more sophisticated theoretical foundation is needed—one that embraces uncertainty and allows for nuanced expert input. This section outlines the core theories and mathematical foundations that underpin the methodology used in this research, with a particular focus on decision-making under uncertainty, neutrosophic logic, and the Fermatean extension.

Multicriteria decision-making (MCDM) forms the foundational approach for this study. MCDM is widely used in contexts where decisions must be made based on multiple conflicting criteria. In educational settings, this might include balancing infrastructure development with faculty training or aligning student engagement strategies with industry collaboration. Traditional MCDM methods such as AHP, TOPSIS, or VIKOR require precise numerical inputs, which makes them less suitable for domains like creative education, where expert evaluations are often subjective and involve hesitation.

To address this limitation, researchers have increasingly adopted fuzzy set theory and its variants, which allow for the modeling of imprecision. Fuzzy sets introduced by Zadeh enable the representation of partial membership rather than binary decisions. While useful, fuzzy logic still lacks a mechanism for explicitly expressing indeterminacy—a key aspect in expert judgment where the truth value may be uncertain, incomplete, or conflicted. This is particularly relevant in evaluating teaching quality, where criteria such as "student creativity" or "curriculum adaptability" do not lend themselves to binary or crisp assessments.

To overcome this, neutrosophic set theory was developed by Smarandache as an extension of fuzzy and intuitionistic fuzzy logic. Unlike its predecessors, neutrosophy introduces a third component—indeterminacy—alongside truth and falsity. This addition provides a more flexible and realistic way to model expert opinions, especially when those opinions are based on experience rather than data. In neutrosophic sets, a value can simultaneously belong to the degrees of truth, indeterminacy, and falsity, allowing for greater expressive power.

Further refinement came with the introduction of interval-valued neutrosophic sets (IVNS). These sets enable each of the three components—truth, indeterminacy, and falsity—to be expressed as intervals rather than fixed numbers. This is especially important when experts are uncertain or hesitant, as they can provide a range of values that better reflect their judgment. IVNS thus bridges the gap between mathematical modeling and human reasoning in complex decision environments.

Building on this, Fermatean neutrosophic sets offer a more recent advancement. These sets retain the three-dimensional structure of neutrosophy but modify the membership conditions to allow for greater flexibility and tolerance of overlapping uncertainty. In a Fermatean neutrosophic environment, the sum of the cubic powers of the truth, indeterminacy, and falsity degrees must be less than or equal to one. This cubic relationship enables more expressive modeling of human hesitation and vague knowledge, particularly when multiple evaluators are involved.

The use of interval-valued Fermatean neutrosophic numbers (IVFNNs), as employed in this research, allows decision-makers to account for the full spectrum of uncertainty in expert evaluations. Each expert's judgment is captured as a set of three intervals—one for each dimension—ensuring that their hesitation, confidence, and ambiguity are preserved in the decision model. This makes the IVFNN approach ideal for evaluating educational risks where qualitative judgments dominate.

To process the collected IVFNN data, an objective weighting technique is required. This study uses Shannon's entropy method, which calculates the degree of disorder or uncertainty in each criterion. A higher entropy value indicates greater uncertainty and lower decision utility, while lower entropy suggests that the criterion provides more useful information. This weighting approach ensures that criteria with higher informational clarity have greater influence on the final rankings.

The final step in the decision-making process involves ranking the alternatives using the MAIRCA method (Multi-Attributive Ideal-Real Comparative Analysis). MAIRCA compares the theoretical ideal performance of each alternative against its actual performance, calculating the deviation or "gap" between expectation and reality. This method is particularly effective in risk evaluation contexts, as it highlights which alternatives (or risk scenarios) deviate most from institutional goals, allowing stakeholders to prioritize areas for improvement.

Together, these theories form a cohesive and robust framework for assessing the complex and uncertain landscape of practical teaching in art and design education. By combining IVFNNs with entropy and MAIRCA, the proposed model captures expert insight in a structured, transparent, and analytically sound way—providing academic leaders with actionable intelligence to inform decision-making and strategic

3.1. MCDM Methods

This section shows the steps of the MCDM methodology.

We can define some definitions of interval valued Fermatean neutrosophic (IVFN) such as[13], [14]:

Definition 1

IVFN set can be defined as:

$$IVFN_{Number} = \left(\left[{T_{r_a}}^{A-}, {T_{r_a}}^{A+}\right], \left[{I_{r_a}}^{A-}, {I_{r_a}}^{A+}\right], \left[{F_{r_a}}^{A-}, {F_{r_a}}^{A+}\right]\right) \quad (1)$$

$$\left({T_{r_a}}^{A+}\right)^3 + \left({I_{r_a}}^{A+}\right)^3 + \left({F_{r_a}}^{A+}\right)^3 \leq 2 \quad (2)$$

$$a = \left(\left[{T_{r_a}}^{A-}, {T_{r_a}}^{A+}\right], \left[{I_{r_a}}^{A-}, {I_{r_a}}^{A+}\right], \left[{F_{r_a}}^{A-}, {F_{r_a}}^{A+}\right]\right) = [a, b], [c, d], [e, f] \quad (3)$$

Let two IVFN as:

$$R = \left\{k, T_{r_R}(k), I_{r_R}(k), F_{r_R}(k)\right\} \quad (4)$$

$$L = \left\{k, T_{r_L}(k), I_{r_L}(k), F_{r_L}(k)\right\} \quad (5)$$

$$T_{r_R}(k) = \left[{T_{r_R}}^{-}(k), {T_{r_R}}^{+}(k)\right] \quad (6)$$

$$I_{r_R}(k) = \left[{I_{r_R}}^{-}(k), {I_{r_R}}^{+}(k)\right] \quad (7)$$

$$F_{r_R}(k) = \left[{F_{r_R}}^{-}(k), {F_{r_R}}^{+}(k)\right] \quad (8)$$

$$T_{r_L}(k) = \left[T_{r_L}{}^{-}(k), T_{r_L}{}^{+}(k)\right] \quad (9)$$

$$I_{r_L}(k) = \left[I_{r_L}{}^{-}(k), I_{r_L}{}^{+}(k)\right] \quad (10)$$

$$F_{r_L}(k) = \left[F_{r_L}{}^{-}(k), F_{r_L}{}^{+}(k)\right] \quad (11)$$

$$T_{r_R}{}^{-}(k) \leq T_{r_L}{}^{-}(k), T_{r_R}{}^{+}(k) \leq T_{r_L}{}^{+}(k) \quad (12)$$

$$I_{r_R}{}^{-}(k) \geq I_{r_L}{}^{-}(k), I_{r_R}{}^{+}(k) \geq I_{r_L}{}^{+}(k) \quad (13)$$

$$F_{r_R}{}^{-}(k) \geq F_{r_L}{}^{-}(k), F_{r_R}{}^{+}(k) \geq F_{r_L}{}^{+}(k) \quad (14)$$

$$D = R \cup L = \left\{k, T_{r_D}(k), I_{r_D}(k), F_{r_D}(k)\right\} \quad (15)$$

$$R \cup L = \begin{Bmatrix} \max\left(T_{r_R}{}^{-}(k), T_{r_L}{}^{-}(k)\right), \max\left(T_{r_R}{}^{+}(k), T_{r_L}{}^{+}(k)\right), \\ \min\left(I_{r_L}{}^{-}(k), I_{r_R}{}^{-}(k)\right), \min\left(I_{r_L}{}^{+}(k), I_{r_R}{}^{+}(k)\right), \\ \min\left(F_{r_L}{}^{-}(k), F_{r_R}{}^{-}(k)\right), \min\left(F_{r_L}{}^{+}(k), F_{r_R}{}^{+}(k)\right) \end{Bmatrix} \quad (16)$$

$$R \cap L = \begin{Bmatrix} \min\left(T_{r_R}{}^{-}(k), T_{r_L}{}^{-}(k)\right), \min\left(T_{r_R}{}^{+}(k), T_{r_L}{}^{+}(k)\right), \\ \max\left(I_{r_L}{}^{-}(k), I_{r_R}{}^{-}(k)\right), \max\left(I_{r_L}{}^{+}(k), I_{r_R}{}^{+}(k)\right), \\ \max\left(F_{r_L}{}^{-}(k), F_{r_R}{}^{-}(k)\right), \max\left(F_{r_L}{}^{+}(k), F_{r_R}{}^{+}(k)\right) \end{Bmatrix} \quad (17)$$

$$L^c = \begin{Bmatrix} \left[F_{r_L}{}^{-}(k), F_{r_L}{}^{+}(k)\right], \\ \left[1 - I_{r_L}{}^{+}(k), 1 - I_{r_L}{}^{-}(k)\right], \\ \left[T_{r_L}{}^{-}(k), T_{r_L}{}^{+}(k)\right] \end{Bmatrix} \quad (18)$$

We show the steps of the entropy method[15], [16].

Create the decision matrix.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}; i = 1, \dots, m; j = 1, \dots, n \quad (19)$$

Compute the normalization of the decision matrix

$$u_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (20)$$

Calculate the entropy value.

$$e_j = -f * u_{ij} \ln u_{ij} \quad (21)$$

$$f = \frac{1}{\ln m} \quad (22)$$

Calculate the criteria weights.

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} 1 - e_j} \quad (23)$$

Then we apply the steps of the MAIRCA method[17], [18].

Determine the elements $q_{p_{ij}}$ of the theoretical rating matrix

$$q_{p_{ij}} = x_{ij} * w_j \tag{24}$$

Calculate the elements of real rating matrix

$$d_{ij} = q_{p_{ij}} \left(\frac{x_{ij} - \min x_i}{\max x_i - \min x_i}\right) \text{ for positive criteria} \tag{25}$$

$$d_{ij} = q_{p_{ij}} \left(\frac{x_{ij} - \max x_i}{\min x_i - \max x_i}\right) \text{ for cost criteria} \tag{26}$$

Calculate the total gap matrix

$$T_{ij} = q_{p_{ij}} - d_{ij} \tag{27}$$

Calculate the final values

$$S_i = \sum_{i=1}^{m} T_{ij} \tag{28}$$

Rank the alternatives.

4. Application of the Proposed Method

This section presents the detailed application of the proposed decision-making framework to evaluate the critical risks affecting the quality of practical teaching in art and design education. The goal is to identify the most influential criteria and rank the risk-based alternatives to guide academic institutions in prioritizing improvement areas.

The framework is applied using nine carefully selected evaluation criteria that reflect key aspects of effective practical education. These include curriculum adaptability, collaboration with industry experts, employment and career preparedness, practical skill assessment, infrastructure and facility support, student engagement strategies, faculty development, financial resource allocation, and health and safety compliance. These criteria were chosen based on their relevance to the operational and pedagogical realities of art and design programs in higher education.

In parallel, nine alternatives were defined. Each represents a real and frequently encountered risk scenario within universities. These alternatives include insufficient studio and lab facilities, low student participation and motivation, lack of regular curriculum updates, ineffective assessment strategies, underqualified faculty in practical training, weak safety regulations in workshops, mismatch between practical training and job market needs, inadequate funding for practical learning, and limited industry collaboration. Each of these alternatives reflects a distinct challenge, such as outdated infrastructure or disconnects between education and employment, which can severely affect the outcomes of practical courses.

To begin the analysis, a decision matrix was developed using input from three academic experts who have direct experience with curriculum design, institutional planning, and teaching in practical environments. These experts evaluated the impact of each alternative on the selected criteria using interval-valued Fermatean neutrosophic numbers. This approach allowed them to express not only certainty but also degrees of hesitation and partial agreement, which is important when dealing with subjective evaluations in qualitative domains like education.

The IVFNN values collected from all three experts were then transformed into crisp values using defuzzification techniques. These crisp values represent the experts' consolidated assessments in a format suitable for further mathematical processing. The complete crisp decision matrix is presented in Table 1. This matrix shows the perceived performance of each alternative under each criterion and provides the foundation for normalization and weight calculation.

The matrix was then normalized using equation 20 to ensure comparability among all criteria regardless of their original scales. The normalized decision matrix, shown in Table 2, adjusts the raw performance values so that they can be interpreted on a common scale. This is a necessary step before calculating entropy values, as it allows for fair comparisons across all nine criteria.

Entropy values were calculated for each criterion using equation 21. The purpose of entropy analysis in this context is to identify which criteria provide the most useful or differentiating information. A criterion that shows high variation among the alternatives contributes more meaningfully to the decision process. In contrast, criteria where all alternatives perform similarly have lower decision value.

The entropy-based weight calculation was then performed using equation 23. The weights for each criterion are shown in Table 3. These weights represent the relative importance of each criterion based on the distribution of the expert evaluations. The results indicate that infrastructure and facility support, and faculty development received the highest weights, with values of 0.144 and 0.137 respectively. This finding is consistent with existing literature and practical experience. Many institutions struggle with outdated or insufficient physical resources, and the lack of professional development opportunities for faculty often results in outdated teaching methods. These issues directly affect the quality of practical teaching and students' ability to apply theoretical knowledge in real-world settings.

In contrast, criteria such as financial resource allocation and health and safety compliance received relatively low weights, around 0.087 and 0.076 respectively. This does not suggest that these areas are unimportant, but rather that there was less variability across the institutions in these aspects, or that their direct impact on learning outcomes is less pronounced in the short term.

It is important to note that even though the differences in weights may appear small numerically, they play a significant role in the next phase of analysis. The weighting results are used to determine the final ranking of the risk scenarios using the MAIRCA method, which considers both the ideal and actual performance of each alternative. The gap between expectation and reality provides insight into the area's most in need of institutional intervention.

The application of this framework allows educational decision-makers to identify where the greatest challenges lie. For example, if an institution finds that the risk related to underqualified faculty ranks highest, this indicates a need to invest in training, hire industry professionals as part-time lecturers, or develop partnerships with external organizations to expose students to current practices. Likewise, if inadequate infrastructure is found to be a top-ranked risk, this highlights the urgency of upgrading studios, workshops, and digital labs.

Overall, the application of the proposed method reveals a clear structure of priorities. It moves beyond general observations to provide actionable insights based on expert input and mathematical analysis. This data-driven approach is essential for institutions aiming to enhance the quality of their practical teaching and align educational outcomes with industry expectations. In the following section, the ranking results will be analyzed in more detail using the MAIRCA method to determine which alternatives pose the greatest threat to educational quality and which areas should be addressed first.

Table 1. The decision matrix.

	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_2	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])
ADA_3	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.82,0.85],[0.9,0.91])
ADA_4	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])
ADA_5	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])
ADA_6	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_7	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])
ADA_8	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_9	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])
	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_2	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.8],[0.85,0.85],[0.9,0.95])
ADA_3	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])

ADA_4	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])
ADA_5	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.8],[0.9,0.92])
ADA_6	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_7	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.85,0.8],[0.9,0.92])
ADA_8	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_9	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.8],[0.85,0.85],[0.9,0.95])
	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_2	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])
ADA_3	([0.8,0.85],[0.85,0.8],[0.9,0.92])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.82,0.85],[0.9,0.91])
ADA_4	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])
ADA_5	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])
ADA_6	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.85,0.9],[0.8,0.8],[0.8,0.85])
ADA_7	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.85,0.9],[0.8,0.8],[0.8,0.85])
ADA_8	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.8,0.8],[0.85,0.85],[0.9,0.95])	([0.85,0.9],[0.8,0.8],[0.8,0.85])	([0.8,0.85],[0.85,0.85],[0.9,0.91])
ADA_9	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.85,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.85],[0.82,0.85],[0.9,0.91])	([0.8,0.85],[0.85,0.85],[0.9,0.91])	([0.8,0.8],[0.85,0.85],[0.9,0.95])

Table 2. The normalization matrix.

	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	0.111789	0.112964	0.110805	0.109418	0.107602	0.112933	0.106509	0.107913	0.112804932
ADA_2	0.112542	0.108662	0.112648	0.112844	0.111642	0.109552	0.110262	0.112674	0.112854294
ADA_3	0.109444	0.109174	0.110805	0.109418	0.108751	0.109192	0.111291	0.109162	0.110959897
ADA_4	0.109682	0.112931	0.111556	0.112795	0.11198	0.11295	0.113715	0.110551	0.109427645
ADA_5	0.110192	0.109789	0.109785	0.108548	0.112366	0.110579	0.113665	0.112213	0.108928223
ADA_6	0.112591	0.110661	0.111296	0.11218	0.112897	0.11119	0.106509	0.113466	0.110437563
ADA_7	0.112542	0.1117	0.111524	0.112073	0.112913	0.111207	0.113681	0.112674	0.108928223
ADA_8	0.108675	0.112332	0.109546	0.111054	0.111747	0.111718	0.113078	0.110294	0.112804932
ADA_9	0.112542	0.111788	0.112034	0.111669	0.110101	0.110679	0.111291	0.111053	0.112854294

Table 3. Criteria weights.

	e_j	w_j	Ranks
ADC_1	4.18E-05	0.089	3

ADC_2	4.25E-05	0.0900271	5
ADC_3	1.64E-05	0.034738	1
ADC_4	4.21E-05	0.08918	4
ADC_5	5.83E-05	0.123482	8
ADC_6	2.8E-05	0.059234	2
ADC_7	0.000138	0.29198	9
ADC_8	5.47E-05	0.115828	7
ADC_9	5.05E-05	0.106963	6

Table 4. The theoretical rating matrix

	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	0.228594717	0.230235	0.226271	0.223244	0.216957	0.230067	0.215645	0.218903	0.230134
ADA_2	0.230134326	0.221468	0.230034	0.230235	0.225104	0.223179	0.223244	0.228561	0.230235
ADA_3	0.223798595	0.22251	0.226271	0.223244	0.219275	0.222445	0.225328	0.221436	0.22637
ADA_4	0.22428628	0.230168	0.227805	0.230134	0.225785	0.230101	0.230235	0.224254	0.223244
ADA_5	0.225328267	0.223765	0.224188	0.221468	0.226563	0.225272	0.230134	0.227625	0.222225
ADA_6	0.23023503	0.225541	0.227274	0.22888	0.227632	0.226517	0.215645	0.230168	0.225305
ADA_7	0.230134326	0.227659	0.227738	0.228662	0.227666	0.22655	0.230168	0.228561	0.222225
ADA_8	0.222225419	0.228947	0.223701	0.226583	0.225315	0.227592	0.228947	0.223732	0.230134
ADA_9	0.230134326	0.227838	0.22878	0.227838	0.221995	0.225475	0.225328	0.225272	0.230235

Table 5. The theoretical rating matrix.

	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	0.18178	0.230235	0.091843	0.045225	-0.05991	0.229059	0	-0.06349	0.227241
ADA_2	0.227241	0	0.230034	0.230235	0.156371	0.021391	0.116276	0.18651	0.230235
ADA_3	0.043957	0.026447	0.091843	0.045225	0	0	0.149547	0	0.117143
ADA_4	0.057709	0.228405	0.147641	0.227491	0.175169	0.230101	0.230235	0.07236	0.028398
ADA_5	0.08729	0.058622	0.017257	0	0.196783	0.083191	0.228546	0.161344	0
ADA_6	0.230235	0.104777	0.128242	0.193493	0.226727	0.120472	0	0.230168	0.086616
ADA_7	0.227241	0.16075	0.145184	0.187629	0.227666	0.121482	0.229109	0.18651	0
ADA_8	0	0.195303	0	0.132192	0.162197	0.15301	0.208731	0.058838	0.227241
ADA_9	0.227241	0.165532	0.183473	0.165532	0.071973	0.089236	0.149547	0.098958	0.230235

Table 6. The theoretical rating matrix.

	ADC_1	ADC_2	ADC_3	ADC_4	ADC_5	ADC_6	ADC_7	ADC_8	ADC_9
ADA_1	0.046814603	0	0.134428	0.17802	0.276871	0.001009	0.215645	0.282396	0.002893
ADA_2	0.002893453	0.221468	0	0	0.068733	0.201788	0.106968	0.042051	0
ADA_3	0.179842067	0.196063	0.134428	0.17802	0.219275	0.222445	0.075781	0.221436	0.109228
ADA_4	0.166577731	0.001763	0.080165	0.002644	0.050616	0	0	0.151893	0.194846
ADA_5	0.138038199	0.165144	0.206932	0.221468	0.029779	0.142081	0.001588	0.066281	0.222225
ADA_6	0	0.120764	0.099032	0.035387	0.000906	0.106045	0.215645	0	0.138688
ADA_7	0.002893453	0.066909	0.082554	0.041033	0	0.105068	0.001059	0.042051	0.222225
ADA_8	0.222225419	0.033644	0.223701	0.094391	0.063118	0.074582	0.020216	0.164894	0.002893
ADA_9	0.002893453	0.062306	0.045306	0.062306	0.150022	0.136239	0.075781	0.126314	0

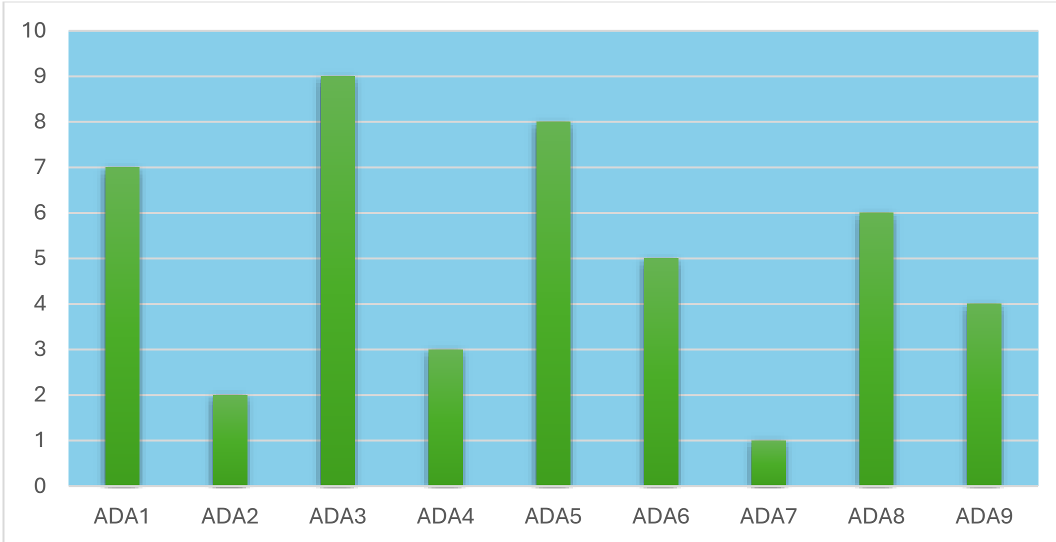

Fig 1. The ranks of the alternatives.

4.1 MAIRCA Results and Ranking of Alternatives

After determining the weights of the criteria using entropy, the next step involves ranking the nine alternatives using the MAIRCA (Multi-Attributive Ideal-Real Comparative Analysis) method. This technique offers a structured and meaningful way to compare each alternative's real performance with its expected or ideal performance, based on the weighted importance of each criterion.

The process begins with the calculation of the theoretical rating matrix. This matrix represents the ideal values that each alternative would achieve under perfect conditions for every criterion, considering their respective weights. These values were computed using equation 24 and are presented in Table 4. This theoretical matrix sets the benchmark for comparison.

Following that, the real rating matrix was generated using equation 25 and is shown in Table 5. This matrix reflects how each alternative actually performs according to the expert evaluations, as filtered through the normalized decision matrix. By comparing the theoretical and real matrices, we can measure how far each alternative deviates from the ideal.

The next step involved calculating the total gap matrix using equation 27. This matrix, found in Table 6, quantifies the difference between the theoretical and real ratings for each alternative across all criteria. A larger gap means a greater discrepancy between expectation and reality, which suggests a more critical risk scenario.

For instance, Alternative 7, which represents "Mismatch Between Practical Training and Job Market Needs," showed one of the highest total gaps in Table 6. This result confirms that many institutions are struggling to align their curricula with the real demands of employers in the creative industries. Students may graduate with strong theoretical knowledge but lack practical exposure to tools, trends, and workflows currently used in the field.

In contrast, Alternative 2, "Low Student Participation and Motivation," had a noticeably smaller total gap, suggesting that while student engagement is a concern, its current state is relatively closer to the desired level compared to other issues.

Using equation 28, the final scores for each alternative were calculated, and the alternatives were ranked accordingly. These final values are visually presented in Figure 1. The scoring reflects the overall performance of each alternative, considering both its deviation from the ideal and the importance of each criterion.

The analysis revealed that Alternative 3, "Lack of Regular Curriculum Updates," received the highest score among all alternatives. This indicates that outdated curricula pose the most significant threat to the quality of practical teaching. This result is supported by real-world observations where some institutions continue to teach design tools and techniques that have been replaced or evolved in professional practice.

On the other end of the spectrum, Alternative 7 received the lowest score. This reinforces the earlier finding that a disconnect between academic training and professional expectations is a major issue that needs urgent attention.

An interesting insight from this ranking is that some alternatives scored similarly and may represent interconnected issues. For example, Alternatives 5 and 9, which correspond to underqualified faculty and limited industry collaboration, both had mid-to-low scores. These issues often coexist, as a lack of industry collaboration may result in faculty not being updated with professional practices, creating a cycle that diminishes teaching quality.

Figure 2 presents the final rankings of all alternatives in a clear comparative format. Institutions can use this information to prioritize interventions. For example, rather than spreading resources evenly across all areas, it would be more strategic to target the top-ranked risks first. Addressing curriculum updates, aligning with job market needs, and investing in faculty development are likely to yield the greatest impact.

This phase of the analysis not only ranks the alternatives but also validates the weight distribution and the expert evaluations used in earlier stages. The consistency of the results across different steps demonstrates the strength of the MAIRCA method in handling complex, uncertain, and qualitative data in the context of educational planning.

In the next section, we will discuss the implications of these rankings and how institutions can apply these insights to enhance the quality of their practical teaching environments.

5. Discussion, Analysis, and Implications

The analysis of practical teaching quality in art and design education using the entropy-weighted MAIRCA method revealed a well-defined hierarchy of risks and challenges. By integrating expert evaluations with a structured decision-making model, the research provided a clear view of which problem areas require urgent attention and which remain relatively stable. However, to ensure the reliability of these rankings and understand how sensitive they are to changes in priorities, a comprehensive sensitivity analysis was also conducted.

The sensitivity analysis aimed to evaluate how variations in the importance assigned to each criterion would affect the final rankings of the nine identified alternatives. These alternatives represent common risk scenarios such as outdated curricula, poor industry collaboration, underqualified faculty, and lack of student engagement. Nine distinct test cases were created. In each case, the weight of one specific criterion was increased by seventeen percent, while the remaining criteria weights were proportionally reduced to maintain balance. This approach simulates real-world conditions where institutional priorities may shift due to changes in funding, leadership, or strategic focus.

After adjusting the weights for each case, the evaluation framework was reapplied. New performance scores for all alternatives were calculated, allowing a comparison across different weighting conditions. The results were visualized in Figures 3 and 4, which display both the score values and the rank order of each alternative in all nine cases. What stood out most was the remarkable consistency in the rankings. Alternative 3, which represents the lack of regular curriculum updates, consistently achieved the highest score across all scenarios. This stability strongly suggests that outdated curricula are universally recognized as the most critical barrier to effective practical education, regardless of how much emphasis is placed on other factors.

Similarly, Alternative 7, which reflects the mismatch between practical training and job market needs, ranked lowest in nearly all cases. This reinforces the concern that many institutions are not effectively aligning their academic content with the evolving demands of the design industry. This disconnect leads to graduates who are unprepared for the types of tools, workflows, and problem-solving approaches required in real-world settings.

These findings validate the robustness of the proposed model. The consistency of rankings, even when criteria weights were intentionally varied, confirms that the method provides dependable guidance for academic planning. It also shows that the most pressing challenges in practical teaching are not isolated or context-dependent but rather systemic issues that persist across different institutional configurations.

From a broader perspective, the results have clear and actionable implications. First, the persistent prominence of curriculum-related risks highlights the need for immediate and strategic curriculum reform. Programs must regularly update their course content to include current technologies, industry-standard tools, and contemporary design thinking. This may involve collaborating with external professionals, adopting modular course structures, or integrating cross-disciplinary content.

Second, the ongoing issue of job market misalignment calls for stronger partnerships between academia and industry. Internships, guest lectures, and real-life project collaborations can provide students with the exposure needed to better understand professional expectations and prepare accordingly. Institutions that neglect this aspect risk producing technically capable but professionally disconnected graduates.

Third, although not always at the top of the rankings, faculty-related issues remain central to the overall success of practical teaching. When instructors lack up-to-date knowledge or hands-on industry experience, even the most modern facilities and well-designed curricula lose effectiveness. Investment in professional development, industry immersion programs for educators, and regular peer review processes can elevate the quality of instruction significantly.

It is also worth noting that some risk factors, such as low student participation or limited health and safety compliance, showed relatively minor impact across most scenarios. This may indicate that institutions have already addressed these areas to a certain extent or that their influence is more indirect. However, they should not be ignored, as they contribute to the overall learning environment and student satisfaction.

Ultimately, the integrated results from both the MAIRCA ranking and the sensitivity analysis confirm that improving practical teaching in art and design requires a multifaceted approach. Addressing a single issue in isolation is unlikely to result in meaningful improvement. Institutions must instead adopt a holistic strategy that considers the dynamic relationships between faculty, students, infrastructure, curriculum, and industry collaboration.

The methodology used in this study offers a reliable, data-driven framework that supports such comprehensive planning. Its ability to account for subjective uncertainty, expert hesitation, and context-specific variation make it particularly well-suited for decision-making in complex educational settings. The results provide not only a snapshot of current weaknesses but also a roadmap for future action, making this model a valuable tool for academic leaders, policy makers, and curriculum developers seeking to enhance the quality and relevance of practical education in the creative disciplines.

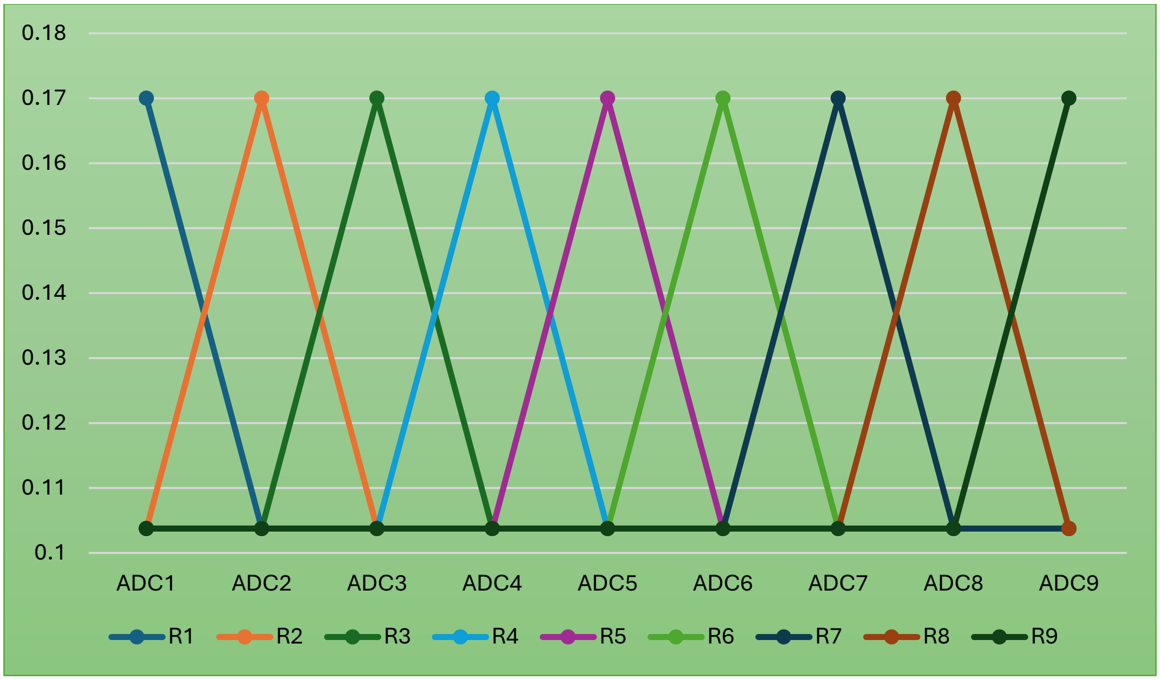

Fig 2. Different criteria weights.

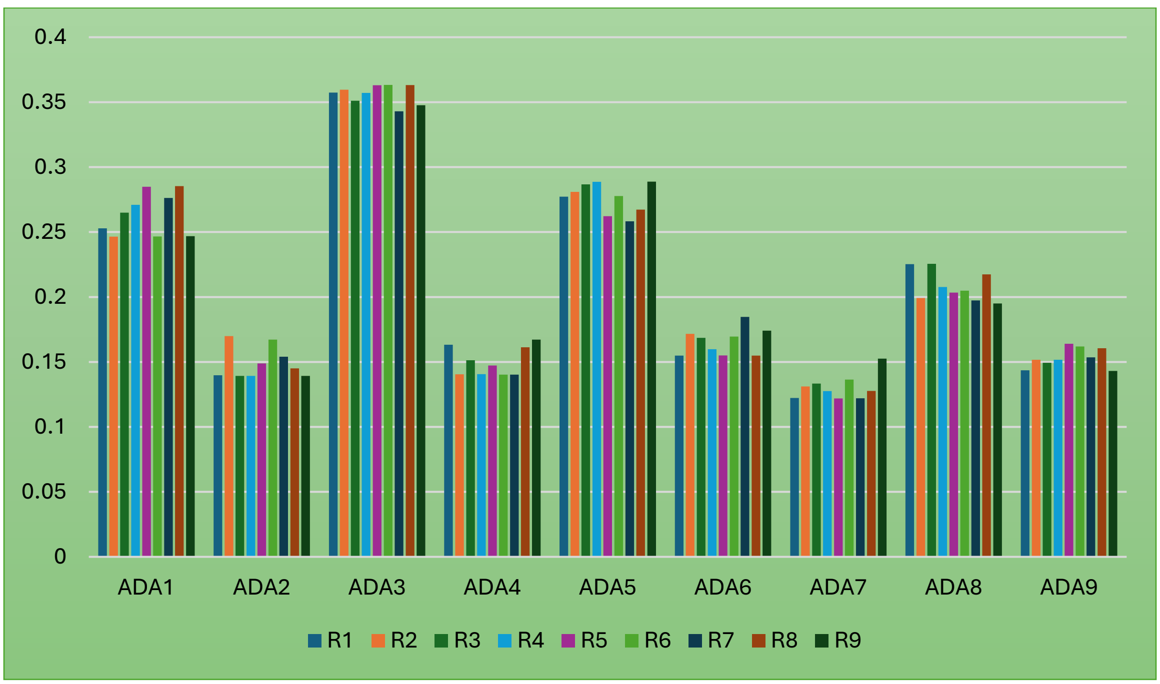

Fig 3. The values of S_i.

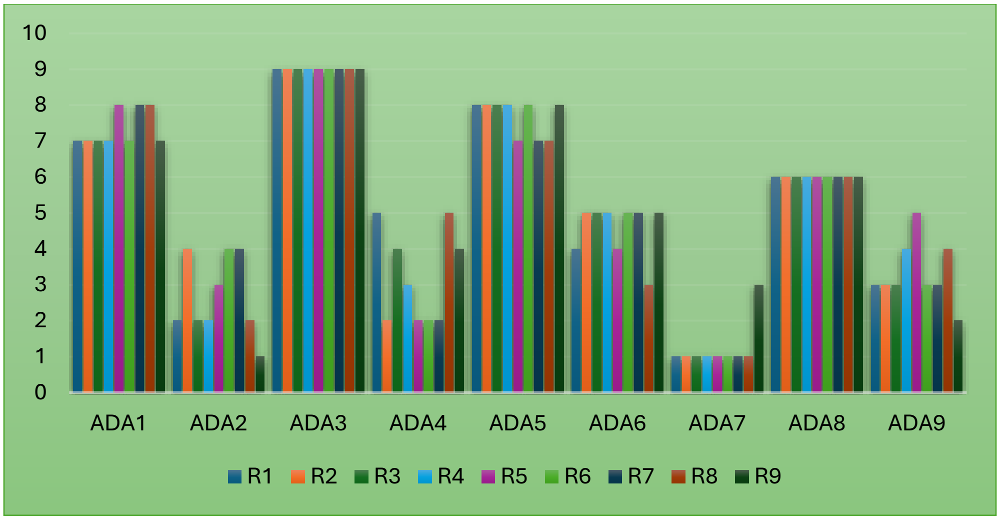

Fig 4. The ranks of the alternatives.

5.1 Managerial and Academic Implications

The findings of this research have practical significance for academic administrators, curriculum designers, and policy makers within institutions offering art and design programs. The ability to prioritize risks based on a structured and data-supported approach enables more targeted planning and resource allocation.

From a managerial perspective, the risk rankings provided by this model can inform budget planning, infrastructure investments, and faculty development initiatives. For example, if "Curriculum Obsolescence" and "Faculty Skill Gaps" are consistently identified as high-risk areas, decision-makers can allocate resources to curriculum renewal committees or initiate training programs for instructors to learn new technologies.

Academically, the model can support ongoing program evaluation and quality assurance. By applying this approach annually or semi-annually, institutions can track changes in performance across criteria and identify emerging risks before they become systemic problems.

Furthermore, the framework promotes transparency and accountability in educational planning. When decisions about where to invest or what to reform are based on clearly defined criteria and expert-driven evaluation, they are more likely to gain support from stakeholders and produce meaningful outcomes.

6. Conclusions

This study set out to address a pressing concern in contemporary art and design education: the growing gap between the expectations of modern creative industries and the realities of practical teaching in academic institutions. As practical learning forms the backbone of design disciplines, any risks that undermine its quality directly affect students' skill development, employability, and long-term professional success.

To evaluate these risks in a structured and meaningful way, we proposed a multi-criteria decision-making model built upon interval-valued Fermatean neutrosophic sets, entropy-based weight calculations, and the MAIRCA ranking method. This integrated framework allowed for a detailed assessment of nine key criteria and nine representative risk scenarios, combining expert judgment with mathematical rigor.

The findings of the study revealed that the most critical risks facing practical teaching today are outdated curricula, disconnects between academic training and market needs, and insufficient faculty development. These issues, while distinct, are deeply interconnected and require coordinated interventions at the policy, institutional, and programmatic levels. In contrast, risks related to student motivation and participation, while important, were found to be relatively less urgent, possibly due to improvements already underway in student-centered learning practices.

The use of entropy and MAIRCA not only enabled precise ranking of risks but also brought attention to the specific areas where institutions can achieve the most impact with targeted reforms. For instance, upgrading infrastructure alone may not lead to better outcomes unless accompanied by updated teaching methods and curricula that reflect current industry standards.

This research contributes both theoretically and practically to the field of educational planning in art and design. Theoretically, it demonstrates how complex, uncertain, and subjective evaluations can be structured into an objective decision-making model without losing their richness. Practically, it offers decision-makers a clear and actionable roadmap for improving the quality of practical teaching in ways that are context-sensitive and strategically aligned with institutional goals.

In future work, the model can be expanded to include more nuanced stakeholder input, such as direct feedback from students and industry professionals. It can also be adapted to other creative disciplines beyond design, including performing arts, media production, and architecture.

Ultimately, improving the quality of practical teaching is not just about minimizing risk—it is about maximizing opportunity. By embracing a data-driven, expert-informed approach, institutions can create more responsive, resilient, and relevant learning environments that prepare students not only to meet the challenges of today's creative economy but to shape their future.

6.1 Limitations and Future Work

While the study presents a novel and effective model for risk evaluation in practical teaching environments, there are certain limitations that should be acknowledged.

First, the expert evaluations used to populate the decision matrix were derived from a small sample. Although the experts were highly experienced in art and design education, expanding the panel to include more diverse voices including students, industry partners, and international educators could enrich the findings and provide broader generalizability.

Second, the study is based on a hypothetical application of the model to simulate risk scenarios. While the analysis is grounded in real-world experiences, applying the model to empirical data from a specific institution or across multiple universities would strengthen its practical value and external validity.

Third, while the sensitivity analysis demonstrated robustness under different weighting conditions, no quantitative comparison with alternative MCDM methods was conducted. Comparing the model's output with results from AHP, TOPSIS, or VIKOR would help validate its performance relative to other established tools.

For future research, several directions are proposed:

1. Apply the model to real institutional data from multiple universities to validate consistency across different contexts.
2. Integrate student feedback and performance metrics into the evaluation criteria for a more holistic assessment.
3. Extend the model to include dynamic risk tracking, where changes in performance are monitored over time.
4. Develop a decision-support system or software tool to automate the use of the model for educational planners.

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