Neutrosophic Sets and Systems, Vol. 83, 2025

University of New Mexico

Smart Education in Action: AI-Based Quality Assessment of Journalism and Media Teaching Practices using the Neutrosophic Cosine Similarity Measure

Feifan Wang[1,2*]

[1]Zhengzhou Technology and Business University, Zhengdong New Area, 450000, Henan, China

[2]Stamford International University, Bangkok, Thailand

*Corresponding author, E-mail: wff3979030@163.com

Abstract: The evolution of artificial intelligence (AI) has sparked a transformative shift in journalism and media education, urging academic institutions to reevaluate traditional pedagogies. As journalism integrates with intelligent tools—from automated news writing to data-driven content curation, there is a rising demand to align teaching quality with emerging media practices. This study presents a comprehensive decision-making framework to assess the quality of teaching practices in journalism and communication programs, addressing the growing intersection of AI and media education. Through multi-criteria decision-making (MCDM) techniques, this research captures the complexities of integrating smart technologies in curriculum delivery, student engagement, and pedagogical innovation. Eight evaluation criteria and eight representative teaching models or institutions are analyzed to offer a holistic view of intelligent teaching quality. The Neutrosophic Cosine Similarity Measure is used to deal with uncertainty information. Two MCDM methods are used, such as DEMATEL method to show the criteria weights and the MARCOS method to rank the alternatives.

Keywords: Neutrosophic Cosine Similarity Measure; Smart Education; Journalism and Media Teaching.

---

1. Introduction

In an era where artificial intelligence permeates all facets of communication, journalism and media education must evolve beyond conventional methods. Traditional lecture-based instruction no longer suffices in preparing students for a landscape dominated by automation, algorithmic curation, and immersive storytelling. Instead, a pedagogical transformation is underway—where digital fluency, interactivity, and intelligent learning environments define quality education[1], [2]. The rapid deployment of AI tools such as natural language generation, deepfake detection, and semantic search engines demands that both educators and students acquire new skillsets. The shift from analog to smart journalism not only changes content delivery but also reshapes the dynamics of student learning outcomes. To ensure quality and relevance, there is an urgent need for educational systems to assess and adapt to these shifts through rigorous evaluation[2], [3].

Smart education offers a robust avenue to monitor, enhance, and individualize media instruction. AI-powered platforms allow for real-time feedback, adaptive learning modules, and predictive performance analytics, giving instructors the ability to refine their teaching techniques based on granular data. However, despite its potential, the effectiveness of these intelligent interventions remains underexamined within journalism [4], [5]. One key challenge in this evolution is establishing reliable benchmarks for quality. What defines effective journalism teaching in the age of AI? Is it the integration of cutting-edge tools, or the ability to foster critical media literacy and ethical judgment? This ambiguity necessitates a structured evaluation framework that captures both technological proficiency and pedagogical substance[6].

Furthermore, the student perspective is critical in defining educational quality in this domain. Engaging learners in digitally mediated environments requires more than technical enhancements—it calls for creativity, inclusiveness, and cultural adaptability. Measuring how students perceive and interact with AI-powered tools becomes a crucial component of any evaluation mechanism[7], [8]. This study adopts a multi-criteria decision-making (MCDM) approach to assess teaching quality across eight AI-augmented journalism programs. By analyzing criteria such as faculty adaptability, content relevance, digital interactivity, and AI-driven assessment systems, we construct a comprehensive model that reflects the nuanced demands of smart education.

Ultimately, this research not only contributes to the theoretical understanding of intelligent teaching quality but also serves as a practical guide for journalism faculties seeking to stay at the forefront of innovation. The results will help bridge the gap between traditional communication pedagogy and the intelligent media environments students will encounter in the field

The relationship between MCDM problems is characterized by the fact that symptoms typically imply a great deal of unreliable, unclear, and contradictory information about a disease. To make the right decisions, we must deal with the ambiguities and contradictions. Experts base their decisions on how well the unknown sample matches the fundamental patterns, which are present in most MCDM decisions difficulties. Each element may have distinct truth-membership, indeterminacy-membership, and falsity-membership functions in certain real-world scenarios. Thus, from a philosophical perspective, Smarandache first put out the idea of a neutrosophic set[9], [10].

Within a universal set X, a neutrosophic set A is separately described by a falsity-membership function FA(x), an indeterminacy-membership function IA(x), and a truth-membership function TA(x). In a neutrosophic set A, however, the non-standard unit interval $]^{-}0, 1^{+}[$ is the domain of definition and range of the functions TA(x), IA(x), and FA(x). This interval is only utilized in philosophical applications, particularly where a distinction between absolute and relative truth/falsity/indeterminacy is needed. TA(x), IA(x), and FA(x) can be defined and their range limited to the usual real unit interval [0, 1] for ease of use in technical applications of the neutrosophic set[11], [12].

To solve various attribute decision-making issues utilizing interval neutrosophic information, the Hamming and Euclidean distances between neutrosophic and their similarity metrics were utilized. Ye [13] also introduced the neutrosophic distance-based similarity metric and used it to solve group decision-making issues with single-valued neutrosophic data. Additionally, Ye [13]employed the Jaccard, Dice, and cosine similarity measures—three vector similarity measures for neutrosophic —to MCDM situations including simplified neutrosophic information[14], [15].

1.1. Problem Statement

As journalism and media education undergo rapid digital transformation, there is an urgent need to reassess how teaching quality is evaluated in such evolving environments. Traditional assessment tools are often ill-equipped to address the complexities of smart education, where AI-driven technologies and interactive digital platforms redefine both teaching methods and student engagement. Moreover, existing evaluation frameworks lack the flexibility to handle subjective expert input, interrelated criteria, and dynamic learning settings. This creates a significant gap in developing fair, transparent, and intelligent models to assess teaching practices in journalism programs. Without such models, institutions may struggle to align their curricula with the skills and technologies shaping the future of media education.

1.2. Research Objectives

This study is designed to achieve the following objectives:

1. To develop a hybrid evaluation framework that integrates DEMATEL, MARCOS, and neutrosophic logic for assessing teaching practices in journalism and media education.
2. To identify and prioritize key criteria that influence teaching effectiveness in AI-enhanced learning environments.
3. Comparing alternative teaching strategies using a structured MCDM approach.
4. To provide a practical decision-support tool that helps academic institutions improve the quality and relevance of their journalism programs.

1.3. Significance of Study

This research makes several important contributions to the field of smart education and journalism teaching. First, it introduces a novel evaluation model that accommodates uncertainty and complex interdependencies between educational criteria—an area often overlooked in traditional assessments. Second, by applying neutrosophic logic within an MCDM framework, the study enhances decision-making quality under vague and ambiguous conditions common in educational settings. Third, the research addresses a critical gap by focusing specifically on journalism and media programs, which require unique pedagogical strategies that combine creativity, ethics, and digital fluency. Finally, the study provides actionable insights for academic leaders, curriculum designers, and educators seeking to adopt AI-driven teaching practices in a structured, data-informed manner.

2. Literature Review

In the age of digital transformation, smart education has emerged as a powerful concept that integrates artificial intelligence (AI) with flexible learning environments to enhance teaching and learning effectiveness. This approach is particularly relevant in disciplines like journalism and media studies, which are rapidly evolving alongside technological advancements. Smart education not only promotes real-time interaction and adaptive learning but also enables the measurement of teaching performance through intelligent systems [1].

The role of AI in educational environments has been explored from various angles. Studies show that AI-based systems can personalize learning, provide immediate feedback, and detect student engagement patterns [2]. In media education, AI is not only a teaching aid but also a subject of instruction. For instance, automated news generation, sentiment analysis, and algorithmic fact-checking are now part of modern journalism curricula [3]. These developments require educators to rethink traditional pedagogical models and adopt AI-driven strategies that reflect current industry demands.

However, assessing the quality of teaching practices in such dynamic settings remains a challenge. Traditional evaluation techniques often lack the flexibility to accommodate uncertainty and subjective inputs. This is where Multi-Criteria Decision-Making (MCDM) frameworks prove useful. MCDM techniques like DEMATEL (Decision-Making Trial and Evaluation Laboratory) and MARCOS (Measurement Alternatives and Ranking according to Compromise Solution) offer structured ways to analyze relationships between evaluation criteria and rank alternatives accordingly [4]. They have been successfully applied in various educational and engineering contexts.

To address the limitations of crisp logic in capturing vague and inconsistent judgments, researchers have increasingly turned to neutrosophic logic. Introduced by Smarandache, neutrosophic logic allows for degrees of truth, indeterminacy, and falsity, which is particularly useful in modeling uncertain expert opinions [19]. Recent research demonstrates how neutrosophic MCDM methods offer improved decision quality by handling ambiguity more effectively than traditional fuzzy systems [20].

A study by Asmaa Elsayed [21] applied the MEREC weighting method within a neutrosophic framework to evaluate smart building selection, showcasing how this approach is transferable across fields. Similarly, Said Broumi et al. [22] demonstrated the effectiveness of neutrosophic decision models in complex planning problems, reinforcing their potential in education where variables are often interrelated and hard to quantify.

Despite the promising outcomes of these approaches, there remains a lack of focus on their application in journalism and media education specifically. Most existing studies concentrate on technical disciplines or generalized educational models. This research addresses that gap by tailoring a neutrosophic MCDM framework to evaluate teaching quality in media programs, taking into account the unique demands of creativity, ethical considerations, and critical thinking.

Furthermore, while some works have applied fuzzy or intuitionistic systems, the integration of neutrosophic logic with DEMATEL and MARCOS in educational evaluation is still emerging. The present study contributes to this growing field by proposing a structured, transparent, and scalable evaluation model adapted for smart education environments in journalism, providing both theoretical depth and practical utility.

3. Neutrosophic Cosise Similarity Measure (NCSM)

In this section the similarity measure defines as[16], [17]:

The neutrosophic set can be called the similarity measure if:

$$0 \leq S(A,B) \leq 1 \tag{1}$$

$$S(A,B) = 1 \; if \; and \; only \; if \; A = B \tag{2}$$

$$S(A,B) = S(B,A) \tag{3}$$

$$if \; A \sqsubseteq B \sqsubseteq C, then \; S(A,C) \leq S(A,B) \; and \; S(A,C) \leq S(B,C) \tag{4}$$

Ye [13], [18]introduced the CSM such as:

$$C_1(A,B) = \frac{1}{n}\sum_{j=1}^{n} \frac{T_A(x_j)T_B(x_j) + I_A(x_j)I_B(x_j) + F_A(x_j)F_B(x_j)}{\sqrt{T_A^2(x_j) + T_A^2(x_j) + F_A^2(x_j)} \sqrt{T_B^2(x_j) + I_B^2(x_j) + F_B^2(x_j)}} \tag{5}$$

$$C_1(A,B)=\frac{1}{n}\sum_{j=1}^{n}\frac{2T_A(x_j)T_B(x_j)+2I_A(x_j)I_B(x_j)+2F_A(x_j)F_B(x_j)}{2\sqrt{T_A^2(x_j)+T_A^2(x_j)+F_A^2(x_j)}\sqrt{T_B^2(x_j)+I_B^2(x_j)+F_B^2(x_j)}}=\frac{1}{n} \tag{6}$$

$$\sum_{j=1}^{n}\frac{T_A^2(x_j)+T_A^2(x_j)+F_A^2(x_j)}{T_A^2(x_j)+T_A^2(x_j)+F_A^2(x_j)}=1 \tag{7}$$

The improved cosine measure:

$$C_1(A,B)=\frac{1}{n}\sum_{j=1}^{n}\cos\left[\frac{\beta\left(\left[\begin{array}{c}|T_A(x_j)-T_B(x_j)|\\ \vee|I_A(x_j)-I_B(x_j)|\\ \vee|F_A(x_j)-F_B(x_j)|\end{array}\right]\right)}{2}\right] \tag{8}$$

$$C_1(A,B)=\frac{1}{n}\sum_{j=1}^{n}\cos\left[\frac{\beta\left(\left[\begin{array}{c}|T_A(x_j)-T_B(x_j)|\\ +|I_A(x_j)-I_B(x_j)|\\ +|F_A(x_j)-F_B(x_j)|\end{array}\right]\right)}{2}\right] \tag{9}$$

$$0\le C_k(A,B)\le 1 \tag{10}$$

$$C_k(A,B)=1\ if\ and\ only\ if\ A=B \tag{11}$$

$$C_k(A,B)=C_k(B,A) \tag{12}$$

$$if\ C\ is\ Neutrosophic\ in\ X\ and\ A\sqsubset B\sqsubset C, then C_k(A,C)\le C_k(A,B)\ and\ C_k(A,C)\le C_k(B,A) \tag{13}$$

The weighted cosine similarity measures

$$C_1(A,B)=\sum_{j=1}^{n} w_j \cos\left[\frac{\beta\left(\begin{bmatrix}|T_A(x_j)-T_B(x_j)|\\+|I_A(x_j)-I_B(x_j)|\\+|F_A(x_j)-F_B(x_j)|\end{bmatrix}\right)}{2}\right] \tag{14}$$

$$C_1(A,B)=\sum_{j=1}^{n} w_j \cos\left[\frac{\beta\left(\begin{bmatrix}|T_A(x_j)-T_B(x_j)|\\+|I_A(x_j)-I_B(x_j)|\\+|F_A(x_j)-F_B(x_j)|\end{bmatrix}\right)}{6}\right] \tag{15}$$

The steps of the DEMATEL method applied in this study begin with the definition of evaluation criteria and possible alternatives. These were identified through consultations with subject experts and supported by insights drawn from relevant literature. Once established, a pairwise comparison process was conducted, allowing experts to assess the relative influence of each criterion on the others.

Based on these judgments, a direct relation matrix (denoted as D) was constructed, capturing the direct impacts between each pair of criteria. To ensure comparability and proper scaling of influence values, this matrix was then standardized using the appropriate normalization procedure. This transformation prepares the data for subsequent analysis steps, where both direct and indirect relationships among criteria are examined to reveal their structural interdependencies.

$$S=\frac{1}{\max\limits_{1\le i\le n}\sum_{j=1}^{n} y_{ij}} \tag{16}$$

$$K=S\times D \tag{17}$$

Compute the total relation matrix.

$$R=K\times(I-K)^{-1} \tag{18}$$

Where I present the identity matrix.

Calculate the sum of each row and column

$$O=\left[\sum_{i=1}^{n} R_{ij}\right]_{1\times n} \tag{19}$$

$$L=\left[\sum_{i=1}^{n} R_{ij}\right]_{1\times n} \tag{20}$$

Draw the cause-and-effect diagram.

Compute the criteria weights based on the total relation matrix. After that, we can rank the alternatives based on the MARCOS method.

Normalize the decision matrix based on the beneficial and non-beneficial criteria.

$$u_{ij} = \frac{y_{ij}}{\max_i y_{ij}} \tag{21}$$

$$u_{ij} = \frac{y_{ij}}{\min_i y_{ij}} \tag{22}$$

Create the weighted normalized decision matrix.

$$q_{ij} = W_j u_{ij} \tag{23}$$

Compute the utility degree values.

$$A_i^+ = \frac{Q_i}{\max_i Q_i} \tag{24}$$

$$A_i^- = \frac{Q_i}{\min_i Q_i} \tag{25}$$

$$Q_i = \sum_{j=1}^{n} q_{ij} \tag{26}$$

Create the utility function

$$f(A_i) = \frac{A_i^+ + A_i^-}{1 + \frac{1 - f(A_i^+)}{f(A_i^+)} + \frac{1 - f(A_i^-)}{f(A_i^-)}} \tag{27}$$

$$f(A_i^+) = \frac{A_i^-}{A_i^+ + A_i^-} \tag{28}$$

$$f(A_i^-) = \frac{A_i^+}{A_i^+ + A_i^-} \tag{29}$$

4. Methodology

This section outlines the research design, data collection methods, evaluation criteria, and the structure of the hybrid MCDM model used in this study. The approach is tailored specifically to address the complexity of evaluating journalism and media teaching practices in smart education settings.

4.1 Research Design

The study follows a structured decision-analysis framework that combines both qualitative and quantitative techniques. It is designed to handle multi-dimensional criteria and subjective inputs from domain experts, which are common in educational evaluation. The methodology integrates expert-based assessments with advanced decision modeling tools to produce objective and actionable outcomes.

4.2 Data Collection and Experts Involved

Data was collected using a structured questionnaire developed specifically for this study. The survey included pairwise comparisons of evaluation criteria, as well as ratings of various teaching alternatives. Participants were selected based on their expertise in journalism education, instructional technology, and academic quality assurance. A total of 12 experts participated, representing both academic institutions and educational consulting bodies. Their feedback was used to populate the MCDM models and validate the relevance of each criterion.

4.3 Evaluation Criteria

The evaluation was based on eight key criteria relevant to smart journalism education. These included instructional adaptability, digital content integration, student engagement, real-time feedback mechanisms, use of AI-based tools, course flexibility, multimedia application, and assessment innovation. These criteria were defined through literature analysis and validated by the expert panel. Each criterion represents a critical dimension of effective teaching in the context of AI-enhanced learning environments.

4.4 MCDM Framework (DEMATEL + MARCOS + Neutrosophic Logic)

To process the expert input and derive meaningful insights, a three-stage hybrid MCDM model was employed:

First, the DEMATEL method was applied to understand the causal relationships between evaluation criteria. This helped determine which factors influence others, allowing a deeper understanding of the system structure.

Second, the MARCOS method was used to rank the teaching alternatives. It evaluates each alternative based on its closeness to the ideal and anti-ideal solutions, providing a balanced assessment of performance.

Finally, neutrosophic logic was incorporated throughout the model to handle the inherent uncertainty in expert judgments. Unlike traditional models, the neutrosophic system captures degrees of truth, indeterminacy, and falsity, making it ideal for handling ambiguous or partially known data.

4.5 Justification of the Hybrid Approach

The chosen hybrid model offers several advantages. DEMATEL provides insight into how different educational factors interact, which is crucial in systems where cause-and-effect relationships are not always linear. MARCOS enhances the reliability of rankings by focusing on both the best and worst possible outcomes. Neutrosophic logic ensures the model remains flexible and robust even when expert judgments are uncertain or partially conflicting.

This integrated framework was selected because it reflects the real-world complexity of evaluating modern teaching practices, especially in journalism programs where creativity, technology, and learner-centered approaches intersect.

5. Results and Discussion

This part shows the results of the proposed approach to obtaining the criteria weights and ranking the alternatives. This study collected eight criteria and eight alternatives as shown in Fig 1.

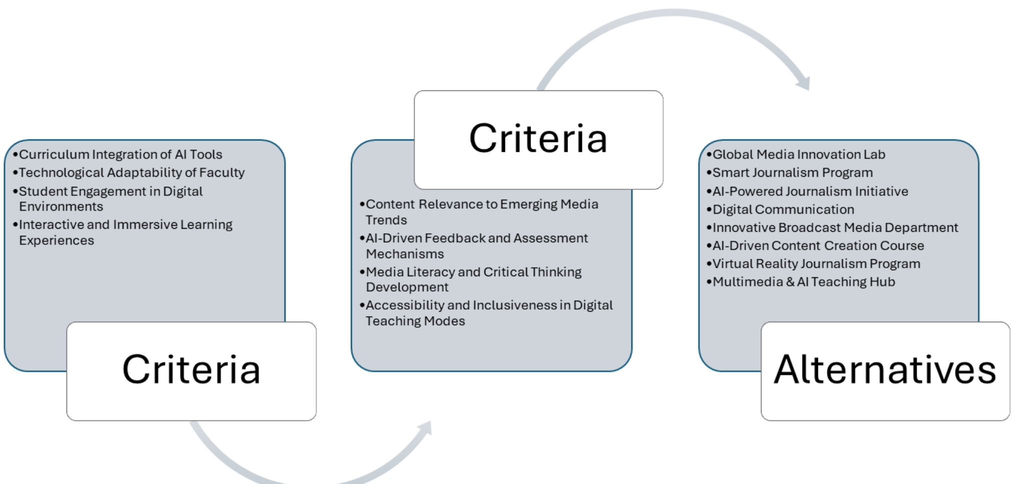

Fig 1. Eight criteria.

To begin the analysis, three domain experts provided comparative judgments among the selected criteria using neutrosophic values, allowing for ambiguity and partial belief to be captured in the evaluation. These judgments formed the foundation of the initial direct relation matrix, which is illustrated in Fig. 2.

This matrix was then normalized to bring all values into a uniform scale using equation (16). The standardized version ensured consistency across the input data and is presented in Fig. 3.

Next, equation (18) was applied to derive the total relation matrix, which extends the analysis by incorporating both immediate and indirect interactions among the criteria. The resulting matrix is shown in Fig. 4.

To further analyze the structure, the aggregate of each row and column was calculated using equation (19). This step highlighted the overall influence and dependency levels for each criterion within the system.

Using these results, a cause-and-effect diagram was generated to visualize how different criteria contribute to or are affected by others. This representation, shown in Fig. 5, clarified the directional flow of influence within the network.

Lastly, the significance of each criterion was quantified through weight determination, based on their total influence scores. The computed weights, as displayed in Fig. 6, played a critical role in the following stages of the evaluation framework.

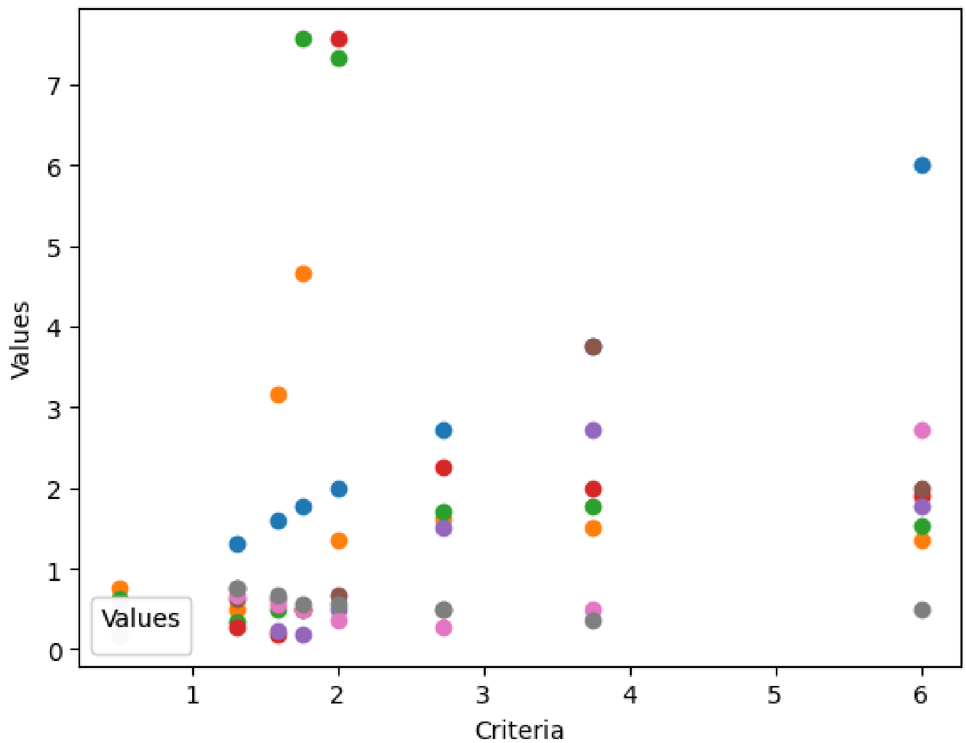

Fig 2. The direct relation matrix.

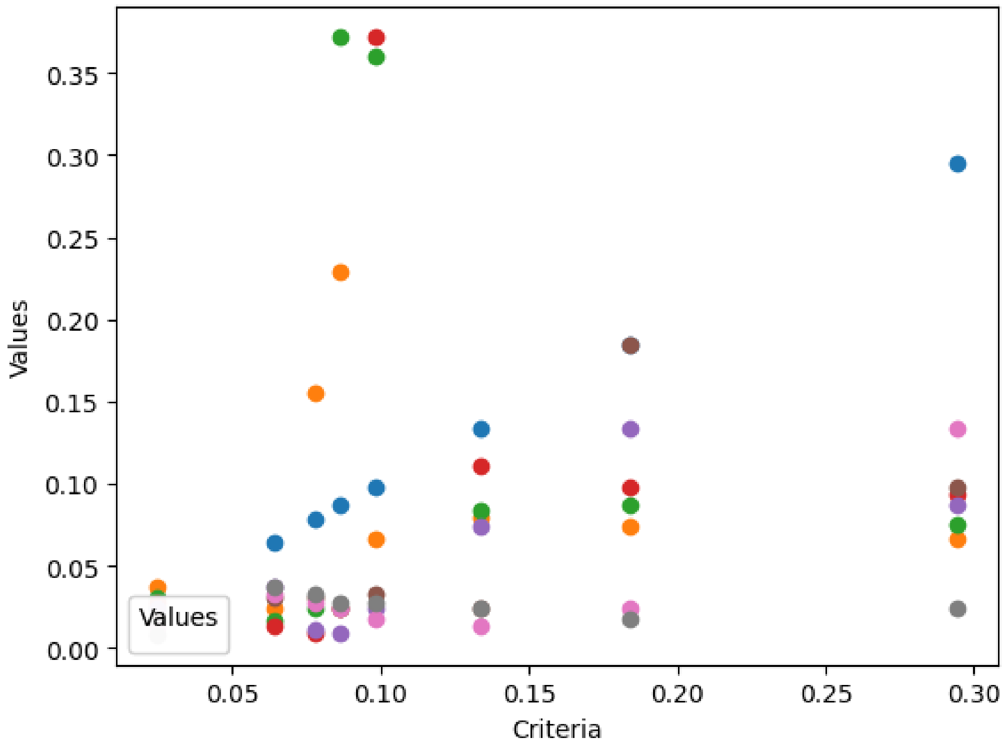

Fig 3. Standardize the direct relation matrix.

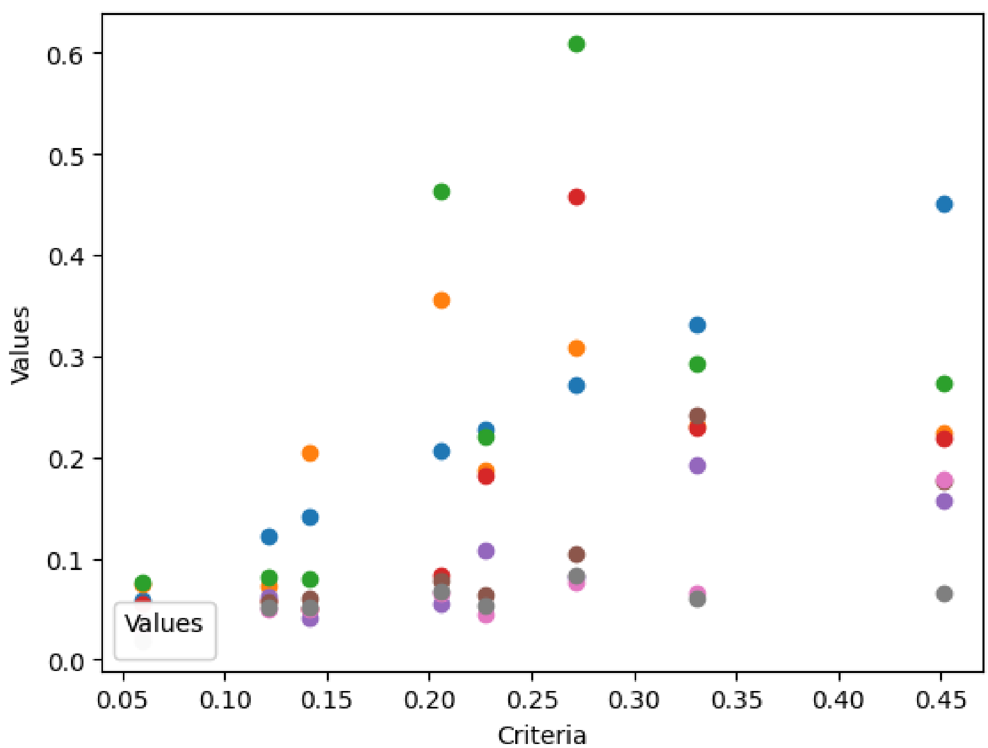

Fig 4. The total relation.

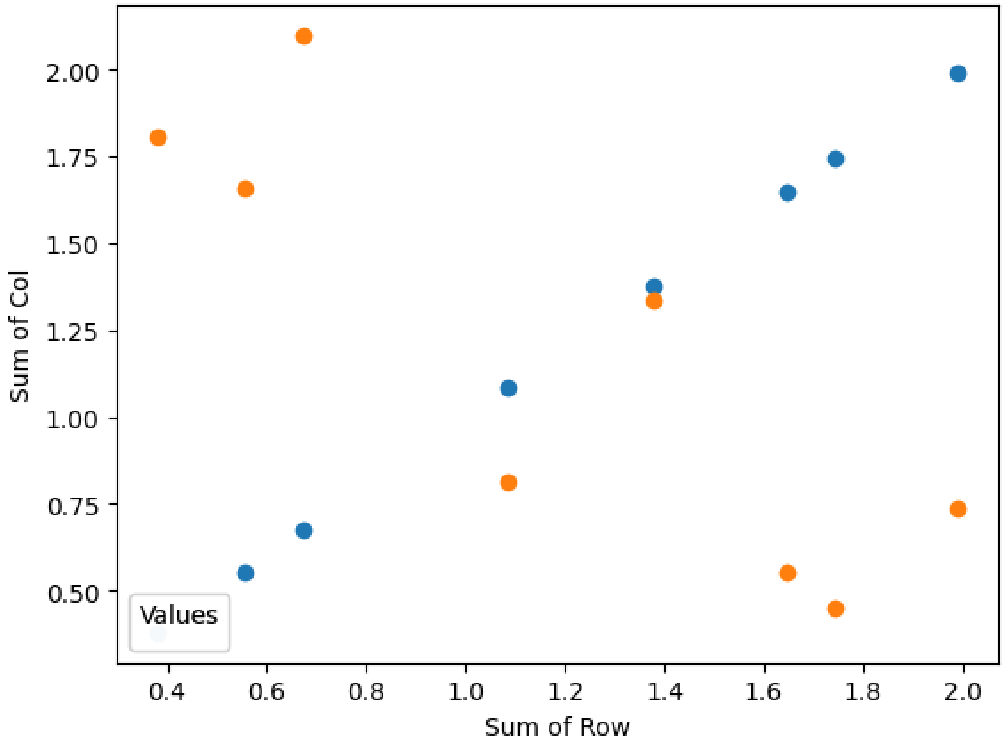

Fig 5. cause-and-effect diagram.

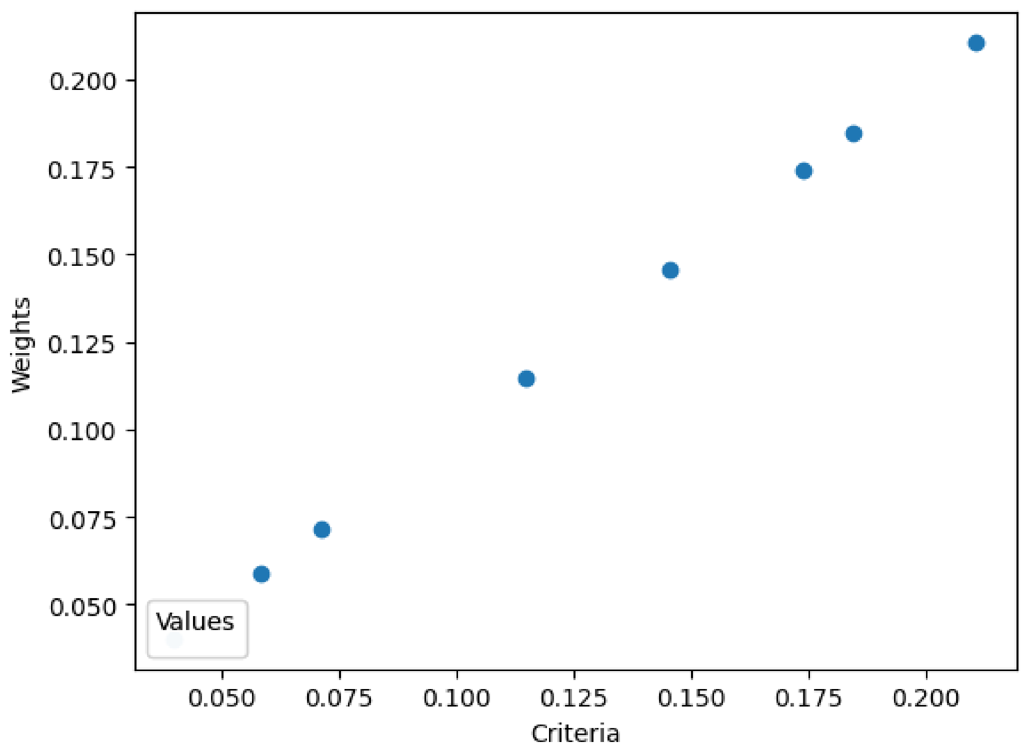

Fig 6. Criteria weights.

To prioritize the teaching alternatives, the MARCOS method was employed as part of the hybrid evaluation framework. The process began by constructing a decision matrix, where expert evaluations were expressed using neutrosophic numbers to account for uncertainty and partial belief. These values were then aggregated using the neutrosophic cosine similarity measure, which provides a meaningful way to compare the alternatives under ambiguous conditions, as shown in Fig. 7.

Following this, the decision matrix was normalized using equation (21), allowing the data to be scaled consistently for comparison, as illustrated in Fig. 8. Next, the normalized values were combined with the criteria weights to produce the weighted normalized decision matrix, applying equation (23), which is presented in Fig. 9.

Subsequently, the utility degree for each alternative was determined using equations (24) through (26). These values represent how closely each alternative approaches the ideal solution, and the results are summarized in Fig. 10. Based on these utility degrees, utility functions were derived using equations (27) to (29), capturing the relative performance of each alternative across all criteria. This step is visualized on Fig. 11.

The final rankings of the alternatives were then established, reflecting their overall effectiveness in meeting the criteria defined for smart journalism education. The results of this ranking are shown in Fig. 12.

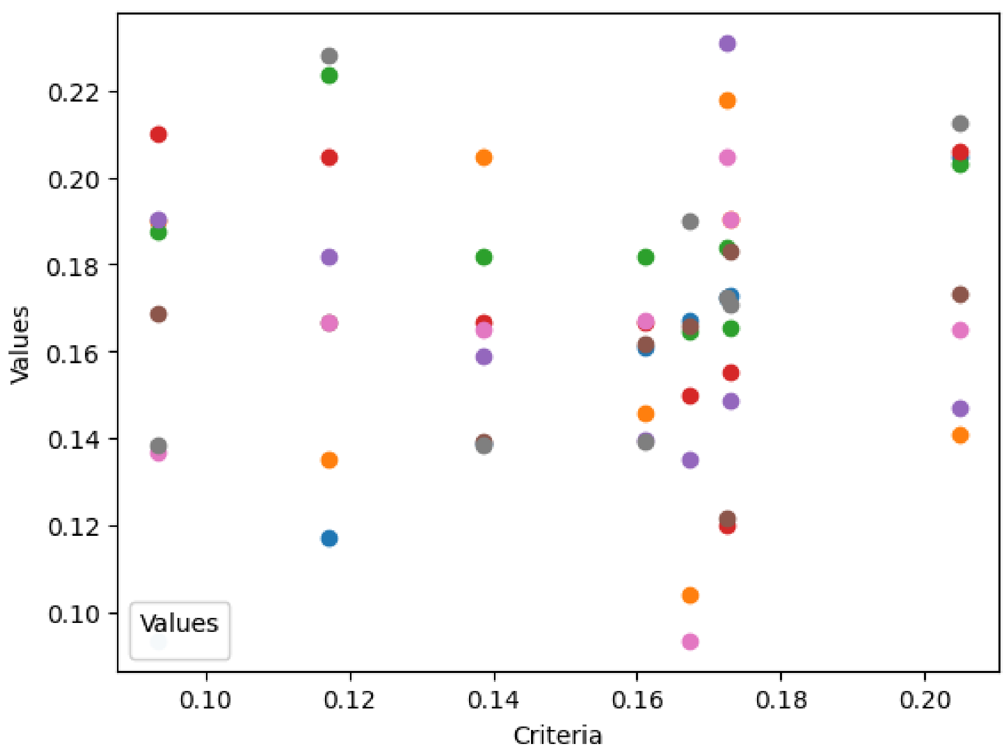

Fig 7. The neutrosophic cosine similarity measure.

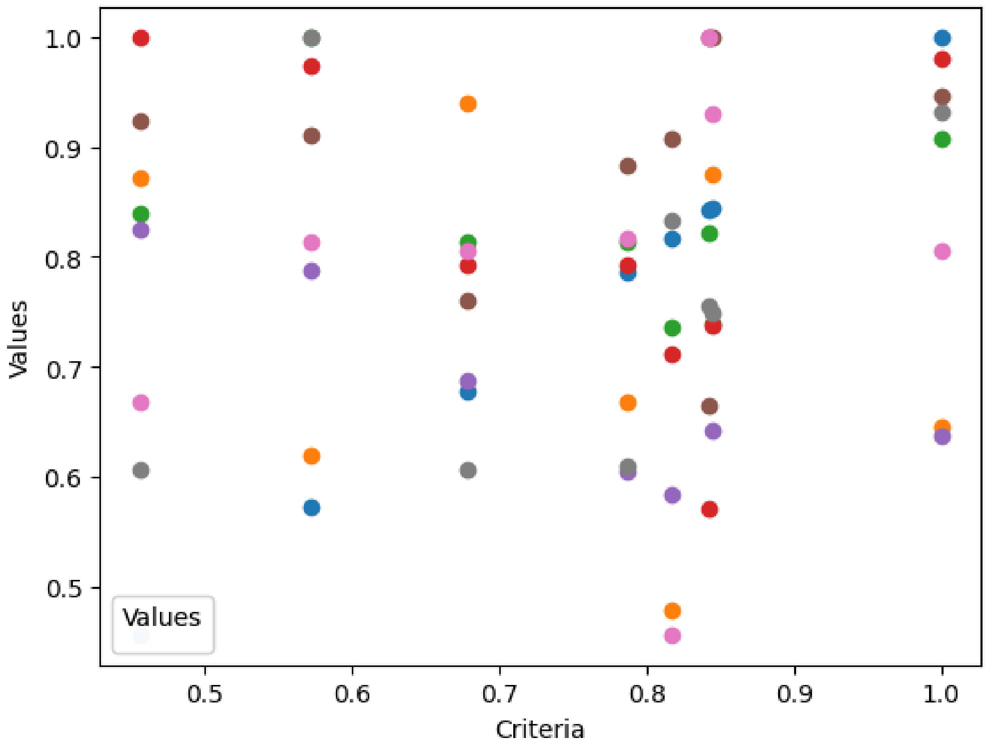

Fig 8. The normalized decision matrix.

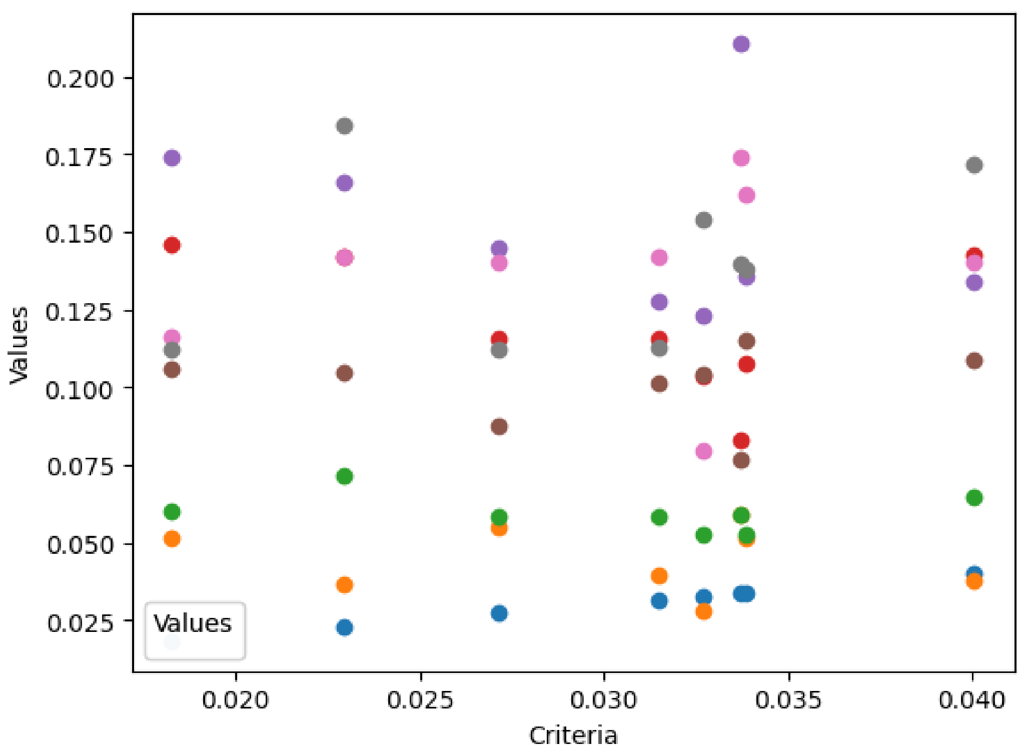

Fig 9. Weighted decision matrix.

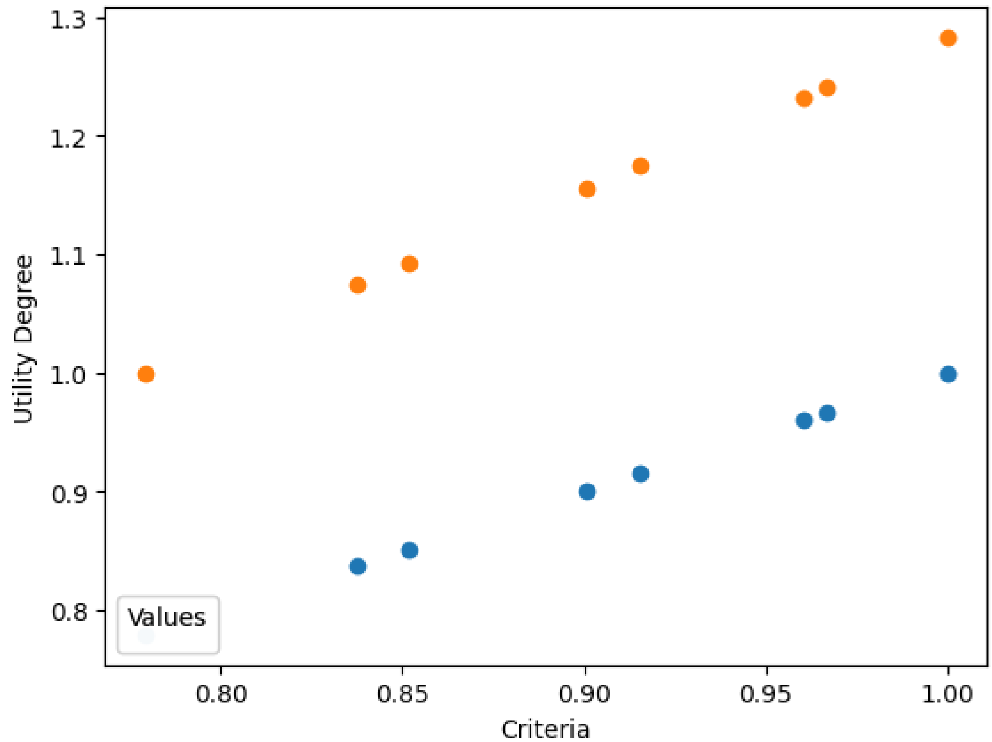

Fig 10. The utility degree values.

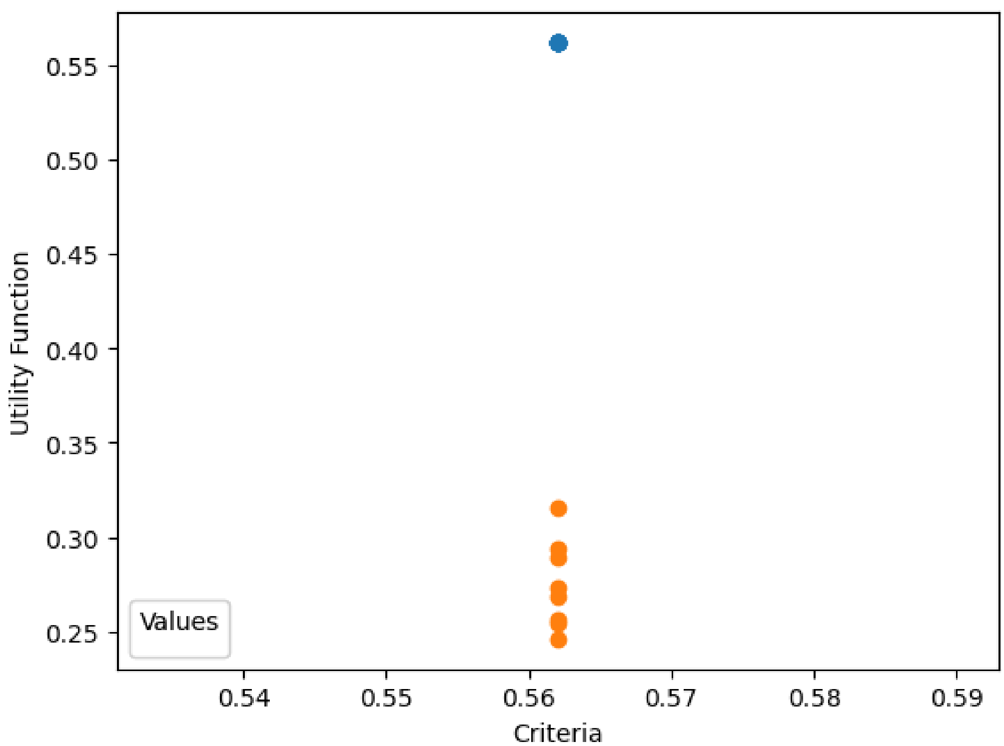

Fig 11. The utility functions.

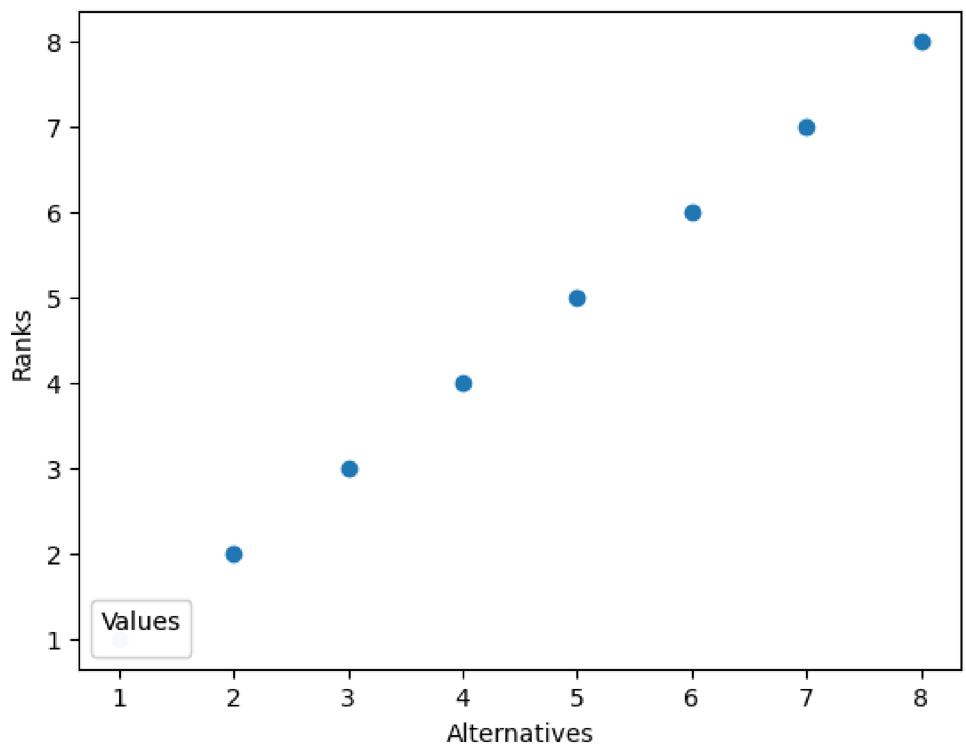

Fig 12. Rank of alternatives.

The analysis conducted in this study provides valuable insight into how AI-supported evaluation models can enhance the quality of journalism and media education. The hybrid MCDM approach revealed that criteria such as digital interactivity, instructional adaptability, and AI-based feedback mechanisms were consistently rated as the most influential. This finding aligns with the growing body of research emphasizing the role of digital transformation in shaping learner-centered environments.

Unlike traditional evaluation tools that rely heavily on rigid metrics, the integration of neutrosophic logic in this study allowed the model to reflect the inherent uncertainty and subjectivity present in expert assessments. By capturing nuanced views, the model produced rankings that were not only data-driven but also contextually grounded in real teaching practices.

Furthermore, the causal mapping provided by the DEMATEL method uncovered how certain pedagogical factors influence one another. For example, the effectiveness of multimedia use was found to be highly dependent on the adaptability of the instructor, highlighting the interplay between technology and pedagogy. These insights suggest that educational quality cannot be assessed in isolation from the tools and environments in which learning occurs. Instead, a more dynamic, interaction-focused approach is

6. Implications

The proposed evaluation framework carries both theoretical and practical significance. Theoretically, it contributes to the development of intelligent decision-making models that accommodate uncertainty in educational quality assessment. By applying neutrosophic logic within a structured MCDM system, the study advances current methodologies in educational evaluation, offering a more realistic approach to modeling complex judgments.

Practically, the framework provides academic institutions with a flexible tool for benchmarking and improving teaching practices. It enables decision-makers to pinpoint which instructional methods align best with modern learning needs and to allocate resources accordingly. The findings may inform curriculum reform, professional development programs, and AI adoption strategies in journalism schools.

Additionally, the ability to model cause-effect relationships among evaluation criteria offers administrators a deeper understanding of how to improve educational outcomes beyond surface-level metrics.

7. Limitations

Despite the robustness of the proposed model, the study has some limitations. The data relied on expert input, which, although well-informed, carries an element of subjectivity that may influence results. The panel size was limited, and while diverse, may not fully represent the range of global journalism education contexts.

Moreover, the criteria and alternatives assessed were specific to a particular educational domain and may require adaptation before being applied in other academic disciplines. The mathematical complexity of the integrated model also presents a barrier to adoption for institutions lacking technical expertise or decision-support infrastructure.

8. Future Work

Future research could expand the model's scope in several directions. First, involving a larger and more globally diverse group of experts would increase the generalizability of the results. Second, integrating student feedback alongside expert opinions could offer a more holistic perspective on teaching effectiveness.

Additionally, future models might incorporate real-time data from digital learning environments to dynamically update teaching quality assessments. This would allow institutions to respond rapidly to instructional challenges and evolving learner needs.

Finally, further development of user-friendly software based on this framework would facilitate broader application, particularly for non-technical users in education administration.

9. Conclusions

The fusion of artificial intelligence and journalism education marks a pivotal shift in how teaching quality should be evaluated and enhanced. By implementing a data-driven, criteria-based framework, institutions can move toward a more responsive and effective educational model. This study highlights the significance of aligning technological innovation with pedagogical intent, ensuring that students are not only equipped with tools but also with the critical thinking skills to use them ethically and effectively. The MCDM methodology is used in this study to deal with differ criteria and alternatives. The DEMATEL methodology is used to obtain the criteria weights, and the MARCOS methodology is used to rank the alternatives. Neutrosophic Cosie similarity measure is used to deal with uncertainty in the decision-making process.

The results affirm that smart education initiatives must be measured holistically, considering not just digital integration but also user engagement, accessibility, and adaptability. As AI continues to shape media landscapes, journalism education must proactively respond with dynamic teaching methods and robust evaluation systems that uphold academic excellence and industry relevance

References

[1] E. Dimitriadou and A. Lanitis, "A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms," *Smart Learn. Environ.*, vol. 10, no. 1, p. 12, 2023.

[2] C. K. Y. Chan, "A comprehensive AI policy education framework for university teaching and learning," *Int. J. Educ. Technol. High. Educ.*, vol. 20, no. 1, p. 38, 2023.

[3] D. Schiff, "Education for AI, not AI for education: The role of education and ethics in national AI policy strategies," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 3, pp. 527–563, 2022.

[4] J.-M. Flores-Viva and F.-J. García-Peñalvo, "Reflections on the Ethics, Potential, and Challenges of Artificial Intelligence in the Framework of Quality Education (SDG4).," *Comun. Media Educ. Res. J.*, vol. 31, no. 74, pp. 35–44, 2023.

[5] M. Jaakkola, "Reporting on artificial intelligence: A handbook for journalism educators," 2023.

[6] K. Pantserev, "Media education in the age of ai and smart media," *Медиаобразование*, no. 3, pp. 507–514, 2021.

[7] F. Pedro, M. Subosa, A. Rivas, and P. Valverde, "Artificial intelligence in education: Challenges and opportunities for sustainable development," 2019.

[8] A. Jha and S. R. Singh, "Integrating Artificial Intelligence in Media Education: Revolutionizing Learning, Creativity, and Critical Thinking," in *Teachers' Roles and Perspectives on AI Integration in Schools*, IGI Global Scientific Publishing, 2025, pp. 297–328.

[9] F. Smarandache, "Foundation of superhyperstructure & neutrosophic superhyperstructure," *Neutrosophic Sets Syst.*, vol. 63, pp. 367–381, 2024.

[10] F. Smarandache, *A unifying field in logics: neutrosophic logic. Neutrosophy, neutrosophic set, neutrosophic probability: neutrsophic logic. Neutrosophy, neutrosophic set, neutrosophic*

probability. Infinite Study, 2005.

[11] J. Ye, "Improved cosine similarity measures of simplified neutrosophic sets for medical diagnoses," *Artif. Intell. Med.*, vol. 63, no. 3, pp. 171–179, 2015.

[12] M. Abdel-Basset, M. Mohamed, M. Elhoseny, F. Chiclana, and A. E.-N. H. Zaied, "Cosine similarity measures of bipolar neutrosophic set for diagnosis of bipolar disorder diseases," *Artif. Intell. Med.*, vol. 101, p. 101735, 2019.

[13] J. Ye, *Vector similarity measures of simplified neutrosophic sets and their application in multicriteria decision making*. Infinite Study, 2014.

[14] P. Biswas, S. Pramanik, and B. C. Giri, "Cosine similarity measure based multi-attribute decision-making with trapezoidal fuzzy neutrosophic numbers," *Neutrosophic sets Syst.*, vol. 8, pp. 46–56, 2015.

[15] E. Bolturk and C. Kahraman, "A novel interval-valued neutrosophic AHP with cosine similarity measure," *Soft Comput.*, vol. 22, no. 15, pp. 4941–4958, 2018.

[16] S. Krishnaprakash, R. Mariappan, and S. Broumi, "Cubic spherical neutrosophic sets and selection of electric truck using cosine similarity measure," *Neutrosophic Sets Syst.*, p. 211, 2024.

[17] L. Wang, Q. Xia, H. Li, and Y. Cao, "Multi-criteria decision making method based on improved cosine similarity measure with interval neutrosophic sets," *Int. J. Intell. Comput. Cybern.*, vol. 12, no. 3, pp. 414–423, 2019.

[18] J. Ye, "Single-valued neutrosophic similarity measures based on cotangent function and their application in the fault diagnosis of steam turbine," *Soft Comput.*, vol. 21, pp. 817–825, 2017.

[19] Smarandache, F. (2005). Introduction to Neutrosophic Logic. American Research Press.

[20] Gul, M., & Ak, M. F. (2022). Comparative evaluation of fuzzy and neutrosophic MCDM approaches in uncertain environments. Neutrosophic Sets and Systems, Vol. 61, pp. 112–126.

[21] Elsayed, A. (2024). Comprehensive Review of MEREC Weighting Method for Smart Building Selection Using Neutrosophic Theory. Neutrosophic Sets and Systems, Vol. 63, pp. 342–366. DOI: 10.5281/zenodo.10535811

[22] Broumi, S., Mukherjee, S., & Biswas, S. (2024). Ranking of Neutrosophic Number Based on Values and Ambiguities and Its Application to Linear Programming Problem. Neutrosophic Sets and Systems, Vol. 63, pp. 203–218. DOI: 10.5281/zenodo.10531801

Received: Nov. 9, 2024. Accepted: April 7, 2025