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Assessing Risk in Teaching: A Fuzzy TOPSIS Approach for Higher Education

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Abstract: - This study addresses the critical challenge of evaluating and mitigating risks associated with various teaching modalities in higher education, particularly as institutions increasingly adopt Online and Hybrid Learning environments. Utilizing the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy TOPSIS), a robust multi-criteria decision-making (MCDM) method, the study systematically assesses and ranks teaching modalities based on five key risk dimensions: technological, operational, pedagogical, compliance, and reputational. Expert evaluations were converted into fuzzy numbers, and distances from the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) were computed to determine each modality's relative performance. The findings reveal that Online Learning is the most effective modality for risk mitigation, particularly excelling in technological, operational, and reputational domains. Hybrid Learning demonstrated balanced performance, ranking second overall, while Face-to-Face instruction was most effective in managing pedagogical and compliance-related risks. These results offer data-driven insights that can guide higher education institutions in optimizing teaching evaluation strategies, improving institutional resilience, and enhancing quality assurance processes. By adopting a structured, evidence-based approach, institutions can better align their instructional delivery with risk management priorities. The study highlights the benefits of integrating Fuzzy TOPSIS in educational decision-making, providing a scalable and transparent framework for continuous improvement

Keywords: Risk-Based, DSS, Teaching and Learning, Fuzzy TOPSIS

I. Introduction

Teaching evaluation plays a vital role in assessing instructional effectiveness, ensuring quality learning experiences, and driving continuous improvement within higher education institutions [1]. With the increasing integration of various instructional modalities—namely Face-to-Face, Online, and Hybrid Learning—there is a growing need to assess the specific risks associated with each approach. These risks encompass technological limitations, operational inefficiencies, pedagogical shortcomings, regulatory compliance issues, and reputational vulnerabilities [2], [3]. As institutions become more dependent on digital platforms for instruction and assessment, understanding the influence of each modality on risk exposure has become critical [4]. While Online Learning offers enhanced flexibility and broader accessibility, it presents challenges related to digital infrastructure, cybersecurity, and student engagement [5]. Hybrid Learning combines traditional and digital approaches but necessitates efficient instructional coordination and optimized resource management [6]. Conversely, Face-to-Face instruction, although conventional, may encounter challenges in maintaining compliance standards and adapting to modern operational constraints [7].

In response to these complexities, this study proposes a systematic, data-driven framework for risk assessment using the Fuzzy Technique for Order of Preference by Similarity to the Ideal Solution (Fuzzy TOPSIS), a recognized multi-criteria decision-making (MCDM) approach [8], [9]. By computing the distances of each alternative from the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS), the study identifies the most effective teaching modality for mitigating risk in teaching evaluation environments [10]. The primary objective is to apply this model to evaluate and rank learning alternatives based on risk factors, thereby supporting evidence-based decision-making. The findings contribute to institutional efforts in quality assurance and strategic risk management. The remainder of this paper is structured as follows: Section II reviews related work, Section III details the methodology, Section IV presents results and analysis, and Section V outlines conclusions and directions for future research.

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II. Related Work

A. Risk Management in Higher Education

Risk management in higher education institutions (HEIs) has become a critical element of institutional governance, particularly in operationally sensitive domains such as the admissions process. The complexity and high-stakes nature of admissions exposes institutions to a broad spectrum of risks, including data privacy violations, IT system failures, cybersecurity threats, and administrative delays. Data breaches involving student records can result in severe regulatory penalties and long-lasting reputational damage. Likewise, system outages during high-demand admission cycles can significantly disrupt processing, undermining institutional credibility and adversely affecting enrollment outcomes.

To mitigate these challenges, researchers have proposed structured risk assessment frameworks specifically adapted to the needs of HEIs. These models incorporate cybersecurity principles and provide tools for systematically identifying and evaluating risks, improving decision-making, and defining appropriate risk acceptance thresholds [11]. Broader operational risks, such as staffing shortages, insufficient faculty training, outdated infrastructure, and limited academic-industry collaboration, also pose significant threats to institutional effectiveness. Addressing these requires comprehensive risk mitigation strategies that align with institutional performance goals and ensure continuity of services [12].

Several studies have extended the discussion on HEI risk management into specific thematic domains. Narayan & Kommunuri [13] explore psychological and socio-cultural factors that drive risk-taking behavior in academic environments, highlighting the role of human vulnerabilities in institutional risk profiles. Odlin et al. [14] propose a typology for internship-related risks, emphasizing the importance of institutional responsibility and operational control in designing mitigation strategies based on frequency and severity. Syamsia et al. [15] analyze operational risks arising from structural conflicts between universities and their governing foundations, recommending context-specific mitigation frameworks. In the area of cybersecurity, Awang et al. [16] advocate for predictive risk assessment methodologies to safeguard campus information systems, while Al-mudaires et al. [17] present an ISO/IEC 27005-aligned framework tailored for governmental educational institutions in Saudi Arabia, addressing gaps in information security compliance and readiness.

Beyond the educational context, Cornwell et al. [18] review the application of data analytics in operational risk management across financial services and energy sectors. Their analysis identifies five core dimensions of risk governance: identification, causal factor analysis, quantification, prediction, and decision-making. These contributions collectively underscore the growing importance of robust, data-driven, and context-specific risk management frameworks tailored to the evolving operational landscapes of higher education institutions.

B. Fuzzy TOPSIS Method

The Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) has emerged as a prominent tool in multi-criteria decision-making (MCDM), particularly suited for addressing uncertainty and vagueness in complex decision environments. By integrating fuzzy set theory into the classical TOPSIS framework, the method evaluates alternatives based on their relative closeness to the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS), providing a structured approach for ranking alternatives across multiple, and often conflicting, criteria. The flexibility and robustness of Fuzzy TOPSIS have led to its widespread application in diverse domains, reflecting its capacity to enhance decision-making accuracy and clarity under uncertainty.

Fuzzy TOPSIS has been utilized in industrial and sustainability-focused applications to evaluate technological and environmental challenges. Tanveer et al. [19] applied the method to assess the impact of digital technologies—such as Cyber-Physical Systems (CPS), the Internet of Things (IoT), Cloud Manufacturing (CM), and Big Data Analytics (BDA)—on circular supply chains within small and medium-sized enterprises (SMEs). Hajiaghaei-Keshteli et al. [20] introduced the Pythagorean Fuzzy TOPSIS to support green supplier selection in food packaging operations by incorporating both environmental and traditional evaluation criteria. Similarly, Alavi et al. [21] developed a dynamic decision support system (DSS) integrating fuzzy Best-Worst Method (BWM) and fuzzy inference systems to optimize sustainable supplier selection in circular supply chains.

In organizational and managerial decision-making, Fuzzy TOPSIS has been employed to support personnel selection and process optimization. Baharin et al. [22] used the method to identify the most suitable managerial candidate based on twelve performance criteria. Govil & Sharma, [23] applied Fuzzy TOPSIS to evaluate software development life cycle (SDLC) models, validating Agile methodologies as the most optimal. Anbarkhan, [24] explored the use of Fuzzy TOPSIS for sustainability evaluation within the context of Industry 5.0 and software engineering practices. In educational and technological assessments, Singh et al. [25] used Fuzzy TOPSIS to rank learning applications based on their effectiveness in promoting critical thinking among novice programming students. Başaran & El Homsi, [26] evaluated six mathematics learning applications using ISO/IEC 25010 software quality standards and a fuzzy TOPSIS approach. Dymova et al. [27] extended the traditional model by introducing an intuitionistic fuzzy TOPSIS integrated with Dempster-Shafer theory to enhance aggregation and manage uncertainty in MCDM scenarios.

Finally, in safety and risk evaluation contexts, Ünlükal & Yücel, [28] combined Intuitionistic Fuzzy TOPSIS with Failure Mode and Effects Analysis (FMEA) to improve the prioritization of risks in aviation industry production processes. These diverse applications collectively underscore the versatility, analytical depth, and sectoral adaptability of Fuzzy TOPSIS in supporting robust, data-driven decision-making across industrial, organizational, environmental, and educational domains.

C. Applications of Fuzzy TOPSIS in Risk Assessment

Fuzzy TOPSIS has demonstrated substantial applicability across various industries, supporting complex risk assessments through its ability to handle uncertainty and multiple conflicting criteria. Its adoption provides organizations with a structured and reliable framework for evaluating and ranking risks, thereby enhancing decision-making, optimizing resource allocation, and promoting more robust risk mitigation strategies. The versatility of Fuzzy TOPSIS is evidenced in its integration across industrial, educational, environmental, and infrastructure sectors. In the industrial and infrastructure domains, several studies have leveraged Fuzzy TOPSIS for advanced risk modelling. Ostadi & Harofteh, [29] developed the Co-Occurrence-based Risk Assessment (CORA) method, which integrates Monte Carlo simulation and system dynamics to assess interconnected risks in a petrochemical project. Similarly, Gu et al. [30] proposed an intuitionistic fuzzy TOPSIS model for assessing rockburst intensity in hydraulic tunnels by analyzing membership degrees in a weighted decision matrix. Awodi et al. [10] utilized fuzzy TOPSIS to evaluate and rank 18 critical risk factors in nuclear decommissioning projects using FPIS, FNIS, and Closeness Coefficients. Cho & Chae, [31] introduced a hybrid decision-making model that integrates TOPSIS with Quality Function Deployment-Failure Mode Effects Analysis (QFD-FMEA) to select construction methods based on safety and environmental risk factors.

Fuzzy TOPSIS has also been effectively applied within educational and organisational management contexts. Kurniawan et al. [32] presented a decision-support framework for evaluating academic department performance based on research output, comparing fuzzy TOPSIS with fuzzy SAW and fuzzy EDAS methods using criteria weighted via the Analytic Network Process (ANP). Xu et al. [33] employed a fuzzy TOPSIS model based on the cloud model to assess student satisfaction with online education across four dimensions—technology, instructor, learner, and environment—during the COVID-19 pandemic. In environmental and policy-focused applications, Sadeghi et al. [34] applied fuzzy TOPSIS with verbal variables to assess industrial risk factors in advanced sectors, offering a structured model for prioritization. Pérez-Pérez et al. [35] utilized a fuzzy logic-based MCDM approach to evaluate climate transition risks within Colombia's processed food industry, emphasizing the role of structured fuzzy assessments in policy and sustainability-driven decision-making

III. METHOD

A. Step 1: Identification of Criteria

The initial step in the Fuzzy TOPSIS methodology involves identifying critical criteria necessary for assessing and prioritizing risks associated with teaching evaluation processes within higher education institutions. Effective identification of relevant risk criteria, such as data privacy violations, IT system failures, and regulatory non-compliance, allows for a comprehensive evaluation framework, enabling institutions to proactively manage potential threats to their teaching evaluation practices. Five principal criteria were systematically selected based on their significance to institutional risk management and their direct implications for ensuring quality and effectiveness in teaching evaluations. These criteria were organized into clearly defined categories, each encompassing specific sub-criteria to address distinct risk dimensions comprehensively. The identified main categories include Compliance and Regulatory Risks, Operational Risks, Pedagogical Risks, Reputational Risks, and Technological Risks. Table 1 summarizes the selected main criteria along with their associated sub-criteria, providing a structured approach that enhances clarity, consistency, and transparency in decision-making.

Table 1: Criteria for Risk Evaluation

Main Criteria	**ID**	**Sub Criteria**
Compliance & Regulatory Risks	C1	Regulatory Non-Compliance
	C2	Policy Breaches
	C3	Data Privacy Violations
Operational Risks	O1	Process Delays
	O2	Resource Constraints
	O3	Errors in Assessment
Pedagogical Risks	P1	Teaching Quality Decline
	P2	Programme Irrelevance
	P3	Student Misconduct
Reputational Risks	R1	Reputation Damage
	R2	CQI Failures
	R3	Health Crises
Technological Risks	T1	System Failures
	T2	Cybersecurity Threats
	T3	Obsolete Technology

B. Step 2: Construct the Decision Matrix

In the second step, decision-makers assigned specific weights and fuzzy values to each identified sub-criterion within the five principal risk categories: Compliance and Regulatory Risks, Operational Risks, Pedagogical Risks, Reputational Risks, and Technological Risks. The fuzzy scale utilized for evaluating the importance of each risk criterion included three defined levels: Low (0.2), Medium (0.4), and High (0.6). Crucial sub-criteria such as Regulatory Non-Compliance, Data Privacy Violations, and Health Crises received ratings ranging from Medium to High due to their substantial potential impact on institutional integrity, regulatory adherence, and stakeholder trust. Conversely, sub-criteria like Process Delays, Errors in Assessment, and Obsolete Technology were predominantly assessed as Low risk, reflecting their relatively minimal influence on institutional performance.

The structured assignment of weights and fuzzy values facilitates the creation of a comprehensive decision matrix, which serves as an analytical foundation for systematically identifying, comparing, and prioritizing critical risks across different learning environments. By clearly articulating the relative significance of each risk sub-criterion, this approach enhances the precision and reliability of risk evaluations, thereby enabling institutions to allocate resources more effectively, improve risk response strategies, and ultimately strengthen overall institutional resilience and decision-making quality. Table 2 illustrates the assigned weights for each sub-criterion, providing transparency and clarity in the analytical process.

Table 2: Characteristics of Criteria

Main Criteria	ID	Sub-Criteria	Weight	Fuzzy Value
Compliance & Regulatory Risks	C1	Regulatory Non-Compliance	Medium	0.4
	C2	Policy Breaches	Low	0.2
	C3	Data Privacy Violations	Medium	0.4
Operational Risks	O1	Process Delays	Low	0.2
	O2	Resource Constraints	High	0.6
	O3	Errors in Assessment	Low	0.2
Pedagogical Risks	P1	Teaching Quality Decline	Medium	0.4
	P2	Programme Irrelevance	Low	0.2
	P3	Student Misconduct	Low	0.2
Reputational Risks	R1	Reputation Damage	Medium	0.4
	R2	CQI Failures	Low	0.2
	R3	Health Crises	High	0.6
Technological Risks	T1	System Failures	Low	0.2
	T2	Cybersecurity Threats	Low	0.2
	T3	Obsolete Technology	Low	0.2

The subsequent phase in the methodology involves assigning fuzzy ratings to each alternative, guided by expert evaluations. Experts employed linguistic terms, specifically Very Low, Low, Medium, High, and Very High, to assess each alternative systematically. These qualitative assessments were subsequently transformed into quantitative fuzzy numbers, providing a structured numerical representation of expert judgments. Table 3 presents the linguistic terms alongside their corresponding fuzzy triangular numbers, defined clearly by lower, middle, and upper bound values. This structured approach enables nuanced capture of expert perceptions, facilitating more precise and reliable comparative evaluations of risk across the learning alternatives.

Table 3: Fuzzy Scale

Code	Linguistic Terms	Lower (L)	Middle (M)	Upper (U)
1	Very Low (VL)	1	1	3
2	Low (L)	1	3	5
3	Medium (M)	3	5	7
4	High (H)	5	7	9
5	Very High (VH)	7	9	9

C. Step 3: Fuzzified Decision Matrix

The third step of the Fuzzy TOPSIS methodology involves constructing the fuzzified decision matrix by converting expert-provided crisp evaluations into fuzzy numbers. Experts assign linguistic ratings—Very Low,

Low, Medium, High, and Very High—to each main criterion and its corresponding sub-criteria. These qualitative ratings are systematically transformed into quantitative fuzzy values, effectively representing uncertainty and variability in expert assessments. Each linguistic term is associated with a triangular fuzzy number comprising a lower bound (L), a middle or most likely value (M), and an upper bound (U). For example, the term High corresponds to the fuzzy number (5, 7, 9), capturing a moderate-to-high intensity range of expert judgment. When an expert rates a sub-criterion under a main criterion as High, it translates directly into the fuzzy triplet (5, 7, 9). This fuzzification approach captures inherent imprecision and variability in human judgment, providing a more nuanced and realistic representation of decision-making processes. The mathematical formula applied for converting crisp expert ratings into fuzzy numbers is defined as follows:

$$\text{Fuzzy Number} = (\mathrm{L}, \mathrm{M}, \mathrm{U}) \tag{1}$$

Where:

L is the lower bound of the fuzzy number,

M is the middle value of the fuzzy number,

U is the upper bound of the fuzzy number.

D. Step 4: Normalized Matrix

Normalization of the decision matrix is essential to achieve consistency and comparability across different evaluation criteria within the Fuzzy TOPSIS methodology. The normalization procedure adjusts the fuzzy numbers assigned to each criterion to a uniform scale, facilitating meaningful comparisons and ensuring that no single criterion disproportionately influences the analysis due to scale discrepancies. Specifically, each fuzzy number is normalized by dividing its lower bound, middle value, and upper bound by the maximum upper bound value identified within the respective criterion. This systematic normalization enhances analytical integrity, reduces bias, and ensures equitable weighting across all evaluated sub-criteria. The mathematical expression for computing the normalized fuzzy decision matrix is presented as follows:

$$\widetilde{r_{ij}} = \left(\frac{l_{ij}}{u_{max}}, \frac{m_{ij}}{u_{max}}, \frac{u_{ij}}{u_{max}}\right) \tag{2}$$

Where:

l_{ij}, m_{ij}, u_{ij} = The fuzzy number's lower, middle, and upper bounds for alternative i under criterion j.

u_{max} = The maximum upper bound within the respective criterion.

E. Step 5: Weighted Normalized Decision Matrix

Following normalization, each normalized fuzzy value is multiplied by the corresponding fuzzy weight assigned to its respective sub-criterion. These weights, defined as Low (0.2), Medium (0.4), or High (0.6), systematically integrate expert judgments regarding the relative importance of each risk factor into the analysis. Applying these fuzzy weights ensures that sub-criteria deemed more impactful receive proportionally greater emphasis in the overall evaluation. The mathematical expression for calculating the weighted normalized fuzzy values is provided as follows:

$$W'_{ij} = X'_{ij} \times w_j \tag{3}$$

Where:

W'_{ij} = The weighted normalized value for alternative i and criterion j,

X'_{ij} = The normalized value for alternative i and criterion j,

W_j = The fuzzy weight for criterion j.

F. Step 6: Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS)

The determination of the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS) constitutes a crucial step in the Fuzzy TOPSIS methodology. These solutions represent the optimal (best-case) and least favourable (worst-case) scenarios, respectively, for each evaluated criterion, thus enabling an effective comparative assessment of alternatives. Specifically, the FPIS is established by selecting the maximum fuzzy values—considering the lower, middle, and upper bounds—for each criterion across all evaluated alternatives. For example, when assessing a criterion such as Impact, the FPIS is computed by identifying the highest fuzzy values from the normalized fuzzy evaluations across all alternatives. This approach facilitates a clear benchmark against which each alternative's performance can be accurately measured. The use of FPIS and FNIS significantly enhances the analytical precision of the decision-making process, providing clear insights into the relative positioning of alternatives. The mathematical formulation for calculating the FPIS for each criterion j is expressed as follows:

$$FPIS_j = \left(\max_i X'_{ij,\text{Lower}},\ \max_i X'_{ij,\text{ middle}},\ \max_i X'_{ij,\text{Upper}}\right) \tag{4}$$

Where:

$\max_i X'_{ij,\text{Lower}}$ = Maximum of the lower bound values for criterion j,

$\max_i X'_{ij,\text{ middle}}$ = Maximum of the middle values for criterion j,

$\max_i X'_{ij,\text{Upper}}$ = Maximum of the upper bound values for criterion j.

Conversely, the Fuzzy Negative Ideal Solution (FNIS) signifies the least favourable scenario for each sub-criterion within the Fuzzy TOPSIS methodology. The FNIS is established by identifying the minimum fuzzy values—encompassing the lower, middle, and upper bounds—for each sub-criterion across all evaluated alternatives. For instance, when evaluating a particular sub-criterion under a main criterion, the FNIS is derived from selecting the lowest fuzzy values observed across all alternatives. This process defines a clear negative benchmark, facilitating an accurate assessment of how distant each alternative is from the least desirable scenario. Utilizing FNIS thus provides critical insights into the potential vulnerabilities and weaknesses of each alternative, enabling institutions to better prioritize interventions and effectively mitigate risks. The mathematical formulation for computing the FNIS for each sub-criterion j is presented as follows:

$$FNIS_j = \left(\min_i X'_{ij,\text{Lower}},\ \min_i X'_{ij,\text{ middle}},\ \min_i X'_{ij,\text{Upper}}\right) \tag{5}$$

Where:

$\min_{\mathrm{i}} \mathrm{X}'_{\mathrm{ij,Lower}}$ = Minimum of the lower bound values for criterion j,

$\min_i X'_{ij,\text{ middle}}$ = Minimum of the middle values for criterion j,

$\min_i X'_{ij,\text{Upper}}$ = Minimum of the upper bound values for criterion j.

G. Step 7: Distance Calculation Results

In Step 7 of the Fuzzy TOPSIS methodology, the distance calculation quantitatively evaluates the proximity of each alternative to the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS). This step provides a structured assessment of how closely each alternative aligns with both ideal and worst-case scenarios across all sub-criteria. Specifically, the Euclidean distance between each alternative's fuzzy ratings and the respective FPIS and FNIS values is calculated. The computation of these distances yields precise numerical indicators, effectively illustrating each alternative's relative strengths and weaknesses. The mathematical expression used for calculating the distance of each alternative from the FPIS is represented as follows:

$$D_i^{FPIS} = \sqrt{\frac{1}{3}\sum_{j=1}^{n}\left(\left(X'_{ij,\text{Lower}} - FPIS_{j,\text{Lower}}\right)^2 + \left(X'_{ij,\text{ middle}} - FPIS_{j,\text{Middle}}\right)^2 + \left(X'_{ij,\text{Upper}} - FPIS_{j,\text{Upper}}\right)^2\right)} \quad (6)$$

Similarly, the distance of each alternative from the FNIS is calculated using the following formula:

$$D_i^{FNIS} = \sqrt{\frac{1}{3}\sum_{j=1}^{n}\left(\left(X'_{ij,\text{Lower}} - FNIS_{j,\text{Lower}}\right)^2 + \left(X'_{ij,\text{ middle}} - FNIS_{j,\text{Middle}}\right)^2 + \left(X'_{ij,\text{Upper}} - FNIS_{j,\text{Upper}}\right)^2\right)} \quad (7)$$

Where:

$\mathrm{D}_{\mathrm{i}}^{\mathrm{FPIS}}$ = The distance of alternative i from the FPIS,

D_i^{FNIS} = The distance of alternative i from the FNIS,

$X'_{ij,\text{Lower}}, X'_{ij,\text{ middle}}, X'_{ij,\text{Upper}}$ = Normalized fuzzy values for alternative i and criterion j,

$FPIS_{j,\text{Lower}}, FPIS_{j,\text{ middle}}, FPIS_{j,\text{Upper}}$ = Fuzzy positive ideal values for criterion j,

$FNIS_{j,\text{Lower}}, FNIS_{j,\text{ middle}}, FNIS_{j,\text{Upper}}$ = Fuzzy negative ideal values for criterion j.

H. Step 8: Closeness Coefficients with Alternative Details

In Step 8, the calculation of the Closeness Coefficient (CC) quantitatively determines each alternative's relative proximity to the Fuzzy Positive Ideal Solution (FPIS) and its distance from the Fuzzy Negative Ideal Solution (FNIS). This coefficient provides a clear numerical indicator reflecting each alternative's overall desirability, with higher values signifying greater closeness to the ideal scenario and increased distance from the worst-case scenario. The Closeness Coefficient serves as a critical analytical measure, enabling institutions to objectively rank alternatives and thus enhance decision-making accuracy, transparency, and strategic alignment.

$$CC_i = \frac{D_i^{FNIS}}{D_i^{FPIS} + D_i^{FNIS}} \quad (8)$$

Where:

CC_i = Closeness Coefficient for alternative I,

D_i^{FNIS} = The distance of alternative i from the FNIS,

D_i^{FPIS} = The distance of alternative iii from the FPIS.

The Closeness Coefficient (CC) values range between 0 and 1, where values approaching 1 signify that the alternative is substantially closer to the Fuzzy Positive Ideal Solution (FPIS) and more distant from the Fuzzy Negative Ideal Solution (FNIS), indicating a highly favourable option. Conversely, values approaching 0 imply that the alternative is closer to the FNIS and farther from the FPIS, denoting a less favourable choice. Each alternative's CC value is computed by evaluating the relative distances to both the FPIS and FNIS obtained in the previous step. Following this calculation, the CC values for all alternatives are systematically compared, enabling the identification of the optimal choice. The alternative possessing the highest CC is recognized as the best solution, given its superior proximity to the ideal outcome and considerable distance from the least desirable scenario.

I. Step 9: Ranking of Alternatives Based on Closeness Coefficient

In Step 9 of the Fuzzy TOPSIS methodology, the alternatives are systematically ranked according to their calculated CC values obtained in the previous step. These CC values quantitatively represent each alternative's relative proximity to the Fuzzy Positive Ideal Solution (FPIS) and its distance from the Fuzzy Negative Ideal Solution (FNIS). Alternatives exhibiting higher CC values are considered more favourable due to their greater closeness to the ideal scenario and greater distance from the least desirable outcome. Consequently, all evaluated alternatives are ordered in descending sequence based on their CC values. The alternative with the highest Closeness Coefficient is ranked first, indicating its superior performance and suitability relative to other choices, while the alternative with the lowest CC is ranked last, reflecting its lower desirability. This systematic ranking process significantly enhances decision-making clarity, ensuring institutions effectively prioritize their options.

IV. Result And Analysis

This section reports the results and subsequent analysis derived from applying the Fuzzy TOPSIS approach to the teaching evaluation process. The assessment systematically evaluates multiple risk factors, specifically technological, operational, pedagogical, compliance, and reputational risks, across three distinct instructional modes: Face-to-Face, Online, and Hybrid Learning. The outcomes elucidate critical strengths and vulnerabilities inherent to each teaching mode, thus providing essential empirical insights for informed decision-making aimed at optimizing strategies in teaching evaluation.

A. Expert in linguistics term

Experts assigned ratings to various risk sub-criteria across three learning environments: Face-to-Face, Online, and Hybrid Learning. These ratings were expressed in linguistic terms and subsequently converted into fuzzy numbers to facilitate systematic analysis. The assessment outcomes enabled the identification of critical risks associated with distinct teaching and learning settings.

Results revealed that Errors in Assessment, Health Crises, and Data Privacy Violations consistently emerged as high or very high risks in all evaluated learning environments. Additionally, System Failures and Policy Breaches were identified as significant risks, especially within Online and Hybrid Learning contexts. Conversely, Process Delays, Student Misconduct, and CQI Failures predominantly received low-risk ratings. Table 4 summarizes the linguistic term ratings provided by the decision-makers.

Table 4: Experts in linguistic term

Sub-Criteria	**Expert1**			**Expert2**			**Expert3**		
	Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
System Failures	VH	M	VH	M	H	M	L	VH	H
Cybersecurity Threats	M	VH	H	L	M	VH	L	H	M
Obsolete Technology	VH	L	M	L	VH	L	M	H	H
Process Delays	L	H	L	L	L	H	L	L	L
Resource Constraints	M	M	VH	L	H	M	M	VH	M
Errors in Assessment	H	VH	H	H	H	VH	VH	VH	VH
Teaching Quality Decline	VH	M	M	M	VH	M	M	M	M
Programme Irrelevance	M	L	VH	VH	M	L	H	H	H

Sub-Criteria	**Expert1**			**Expert2**			**Expert3**		
	Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
Student Misconduct	M	H	L	L	L	H	H	L	L
Regulatory Non-Compliance	H	M	M	M	H	M	H	H	H
Policy Breaches	M	VH	H	H	M	VH	VH	H	H
Data Privacy Violations	VH	L	VH	VH	VH	L	H	VH	VH
Reputation Damage	M	H	L	L	M	H	H	H	M
CQI Failures	L	M	M	M	L	M	H	H	H
Health Crises	H	VH	H	H	H	VH	VH	H	H

B. Step 1: Fuzzified Decision Matrix

The fuzzified decision matrix is established by transforming linguistic terms from Table 4 into corresponding fuzzy numbers according to the fuzzy scale presented in Table 3. Each linguistic term—Very Low, Low, Medium, High, and Very High—is represented by a triangular fuzzy number comprising lower, middle, and upper values (L, M, U). For instance, an expert rating of Very High (VH) corresponds to the fuzzy number (7, 9, 9), while a Medium (M) rating translates to (3, 5, 7), and a Low (L) rating converts to (1, 3, 5). This conversion procedure is consistently applied across all sub-criteria and teaching environments (Face-to-Face, Online, and Hybrid Learning) for each participating expert.

Table 5: Fuzzified Decision Matrix

Main Criteria	**Sub-Criteria**	**Expert1**			**Expert2**			**Expert3**		
		Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
Technological Risks	System Failures	(7, 9, 9)	(3, 5, 7)	(7, 9, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 4)	(7, 9, 9)	(5, 7, 9)
	Cybersecurity Threats	(3, 5, 7)	(7, 9, 9)	(5, 7, 9)	(1, 3, 4)	(3, 5, 7)	(7, 9, 9)	(1, 3, 4)	(5, 7, 9)	(3, 5, 7)
	Obsolete Technology	(7, 9, 9)	(1, 3, 4)	(3, 5, 7)	(1, 3, 4)	(7, 9, 9)	(1, 3, 4)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)
Operational Risks	Process Delays	(1, 3, 4)	(5, 7, 9)	(1, 3, 4)	(1, 3, 4)	(1, 3, 4)	(5, 7, 9)	(1, 3, 4)	(1, 3, 4)	(1, 3, 4)
	Resource Constraints	(3, 5, 7)	(3, 5, 7)	(7, 9, 9)	(1, 3, 4)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(7, 9, 9)	(3, 5, 7)

Main Criteria	Sub-Criteria	Expert1			Expert2			Expert3		
		Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
	Errors in Assessment	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)
Pedagogical Risks	Teaching Quality Decline	(7, 9, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(7, 9, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
	Programme Irrelevance	(3, 5, 7)	(1, 3, 4)	(7, 9, 9)	(7, 9, 9)	(3, 5, 7)	(1, 3, 4)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
	Student Misconduct	(3, 5, 7)	(5, 7, 9)	(1, 3, 4)	(1, 3, 4)	(1, 3, 4)	(5, 7, 9)	(5, 7, 9)	(1, 3, 4)	(1, 3, 4)
Compliance & Regulatory Risks	Regulatory Non-Compliance	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
	Policy Breaches	(3, 5, 7)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)
	Data Privacy Violations	(7, 9, 9)	(1, 3, 4)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(1, 3, 4)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)
Reputational Risks	Reputation Damage	(3, 5, 7)	(5, 7, 9)	(1, 3, 4)	(1, 3, 4)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
	CQI Failures	(1, 3, 4)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(1, 3, 4)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
	Health Crises	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)

C. Step 2:Normalized Matrix

Due to inherent digital vulnerabilities, Online Learning exhibits elevated technological risks, notably Cybersecurity Threats and Obsolete Technology. Conversely, Face-to-Face Learning presents comparatively lower technological risks but experiences heightened operational challenges, including Process Delays and Resource Constraints. Hybrid Learning occupies an intermediate position, encompassing risks associated with both traditional and digital environments. In the domain of Pedagogical Risks, Online and Hybrid Learning modes highlight pronounced concerns such as Teaching Quality Decline and Programme Irrelevance, adversely affecting learner engagement and instructional effectiveness. Compliance and Regulatory Risks, specifically Regulatory Non-Compliance and Data Privacy Violations, are significantly intensified in digital learning contexts due to challenges in policy enforcement. Furthermore, Reputational Risks, such as Reputation Damage and Continuous Quality Improvement (CQI) Failures, emerge as more prominent in Online and Hybrid Learning, directly impacting institutional credibility. Table 6 illustrates the Fuzzified Decision Matrix, summarizing expert assessments of risks across Face-to-Face, Online, and Hybrid Learning modes. To illustrate the normalization process, the fuzzy values assigned by Expert1, Expert2, and Expert3 for the System Failures sub-criterion within the Technological Risks category are provided as follows:

- Expert1: Face-to-Face: (7,9,9), Online: (3,5,7), Hybrid Learning: (7,9,9)
- Expert2: Face-to-Face: (3,5,7), Online: (5,7,9), Hybrid Learning: (3,5,7)
- Expert3: Face-to-Face: (1,3,4), Online: (7,9,9), Hybrid Learning: (5,7,9)

u_{max} = max(9,7,9,7,9,7,4,9,9)=9

System Failures for Face-to-Face for Expert1 = $\widetilde{r_{11}} = \left(\frac{7}{9}, \frac{9}{9}, \frac{9}{9}\right) = (0.7778, 1.0000, 1.0000)$

Table 6: Normalized Matrix

Main Criteria	Sub-Criteria	Expert1			Expert2			Expert3		
		Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
Technological Risks	System Failures	(0.7778, 1.0000, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.1111, 0.3333, 0.4444)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)
	Cybersecurity Threats	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.3333, 0.5556, 0.7778)
	Obsolete Technology	(0.7778, 1.0000, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.3333, 0.5556, 0.7778)	(0.1111, 0.3333, 0.4444)	(0.7778, 1.0000, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)
Operational Risks	Process Delays	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)
	Resource Constraints	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.3333, 0.5556, 0.7778)
	Errors in Assessment	(0.5556, 0.7778, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)

Main Criteria	Sub-Criteria	Expert1			Expert2			Expert3		
		Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
Pedagogical Risks	Teaching Quality Decline	(0.7778, 1.0000, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)
	Programme Irrelevance	(0.3333, 0.5556, 0.7778)	(0.1111, 0.3333, 0.4444)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)
	Student Misconduct	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.1111, 0.3333, 0.4444)
Compliance & Regulatory Risks	Regulatory Non-Compliance	(0.5556, 0.7778, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)
	Policy Breaches	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.3333, 0.5556, 0.7778)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)
	Data Privacy Violations	(0.7778, 1.0000, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.1111, 0.3333, 0.4444)	(0.5556, 0.7778, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)
Reputational	Reputation	(0.3333, 0.5556, 0.7778)	(0.5556,	(0.1111, 0.3333, 0.4444)	(0.1111,	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778	(0.5556, 0.777	(0.3333, 0.5556, 0.7778)

Main Criteria	Sub-Criteria	Expert1			Expert2			Expert3		
		Face-to-Face	Online	Hybrid Learning	Face-to-Face	Online	Hybrid Learning	Face-to-Face	Online	Hybrid Learning
Risks	Damage		0.7778, 1.0000)		0.3333, 0.4444)			, 1.0000)	8, 1.0000)	
	CQI Failures	(0.1111, 0.3333, 0.4444)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.3333, 0.5556, 0.7778)	(0.1111, 0.3333, 0.4444)	(0.3333, 0.5556, 0.7778)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)
	Health Crises	(0.5556, 0.7778, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.7778, 1.0000, 1.0000)	(0.5556, 0.7778, 1.0000)	(0.5556, 0.7778, 1.0000)

D. Step 3: Weighted Normalized Matrix

In Step 3, the weighted normalized matrix is derived by multiplying the normalized fuzzy values of each sub-criterion by their respective weights. For instance, the sub-criterion Health Crises within the Face-to-Face Learning environment initially has a fuzzified value of (5,7,9) from the fuzzified decision matrix. Upon normalization, these values become (0.556,0.778,1). Utilizing the assigned weight of 0.6 from Table 2, the weighted normalized fuzzy values are computed using the following calculation:

$$W'_{ij} = (0.556{,}0.778{,}1) \times 0.6$$

$$W'_{ij} = (0.333{,}0.467{,}0.6)$$

Therefore, the final weighted normalized fuzzy value obtained for the Health Crises sub-criterion within the Face-to-Face Learning environment is (0.333, 0.467, 0.6). This procedure is systematically applied to each sub-criterion, resulting in the construction of a comprehensive Weighted Normalized Matrix. Table 7 summarizes the completed Weighted Normalized Matrix derived from expert evaluations across all learning modes and sub-criteria.

Table 7: Weighted Normalized Matrix

Main Criteria	Sub-Criteria	Expert1			Expert2			Expert3		
		Face-to-Face	Online	Hybrid Learning	Face-to-Face	Online	Hybrid Learning	Face-to-Face	Online	Hybrid Learning
Technological Risks	System Failures	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1111, 0.1556, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)

Main Criteria	**Sub-Criteria**	**Expert1**			**Expert2**			**Expert3**		
		Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
	Cybersecurity Threats	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0667, 0.1111, 0.1556)
	Obsolete Technology	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0667, 0.1111, 0.1556)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)
Operational Risks	Process Delays	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)
	Resource Constraints	(0.2000, 0.3334, 0.4667)	(0.2000, 0.3334, 0.4667)	(0.4667, 0.6000, 0.6000)	(0.0667, 0.2000, 0.2666)	(0.3334, 0.4667, 0.6000)	(0.2000, 0.3334, 0.4667)	(0.2000, 0.3334, 0.4667)	(0.4667, 0.6000, 0.6000)	(0.2000, 0.3334, 0.4667)
	Errors in Assessment	(0.1111, 0.1556, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1556, 0.2000, 0.2000)
Pedagogical Risks	Teaching Quality Decline	(0.3111, 0.4000, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.3111, 0.4000, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)
	Programme Irrelevance	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.1556, 0.2000, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)

Main Criteria	Sub-Criteria	Expert1			Expert2			Expert3		
		Face-to-Face	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**	**Face-to-Face**	**Online**	**Hybrid Learning**
	Student Misconduct	(0.0667, 0.1111, 0.1556)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)
Compliance & Regulatory Risks	Regulatory Non-Compliance	(0.2222, 0.3111, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.2222, 0.3111, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.2222, 0.3111, 0.4000)	(0.2222, 0.3111, 0.4000)	(0.2222, 0.3111, 0.4000)
	Policy Breaches	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)
	Data Privacy Violations	(0.3111, 0.4000, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.3111, 0.4000, 0.4000)	(0.3111, 0.4000, 0.4000)	(0.3111, 0.4000, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.2222, 0.3111, 0.4000)	(0.3111, 0.4000, 0.4000)	(0.3111, 0.4000, 0.4000)
Reputational Risks	Reputation Damage	(0.1333, 0.2222, 0.3111)	(0.2222, 0.3111, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.0444, 0.1333, 0.1778)	(0.1333, 0.2222, 0.3111)	(0.2222, 0.3111, 0.4000)	(0.2222, 0.3111, 0.4000)	(0.2222, 0.3111, 0.4000)	(0.1333, 0.2222, 0.3111)
	CQI Failures	(0.0222, 0.0667, 0.0889)	(0.0667, 0.1111, 0.1556)	(0.0667, 0.1111, 0.1556)	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.0667, 0.1111, 0.1556)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)
	Health Crises	(0.3334, 0.4667, 0.6000)	(0.4667, 0.6000, 0.6000)	(0.3334, 0.4667, 0.6000)	(0.3334, 0.4667, 0.6000)	(0.3334, 0.4667, 0.6000)	(0.4667, 0.6000, 0.6000)	(0.4667, 0.6000, 0.6000)	(0.3334, 0.4667, 0.6000)	(0.3334, 0.4667, 0.6000)

E. Step 4: FPIS (Fuzzy Positive Ideal Solution) and FNIS (Fuzzy Negative Ideal Solution)

Table 8 displays the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) for each sub-criterion across the five primary risk categories: Technological Risks, Operational Risks, Pedagogical Risks, Compliance and Regulatory Risks, and Reputational Risks. These values are computed based on expert evaluations across Face-to-Face, Online, and Hybrid Learning environments. To establish the FPIS for Health Crises under Face-to-Face Learning, maximum fuzzy values for the lower, middle, and upper bounds are identified from expert assessments. The FPIS denotes the most favourable scenario for this sub-criterion. According to the Weighted Normalized Matrix, Expert1, Expert2, and Expert3 consistently assigned identical fuzzy values of (0.4667, 0.6000, 0.6000) to Health Crises. Consequently, the FPIS for this sub-criterion is defined as (0.4667, 0.6000, 0.6000). Conversely, the FNIS is determined by selecting the minimum fuzzy values for the lower, middle, and upper bounds across all experts, representing the least favourable scenario. A similar consistency in expert evaluations results in uniform fuzzy values of (0.3334, 0.4667, 0.6000). Therefore, the FNIS for Health Crises under Face-to-Face Learning is established as (0.3334, 0.4667, 0.6000).

Table 8: FPIS (Fuzzy Positive Ideal Solution) and FNIS (Fuzzy Negative Ideal Solution)

Main Criteria	**Sub-Criteria**	**Expert1**		**Expert2**		**Expert3**	
		FPIS	**FNIS**	**FPIS**	**FNIS**	**FPIS**	**FNIS**
Technological Risks	System Failures	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1111, 0.1556, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)
	Cybersecurity Threats	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)
	Obsolete Technology	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0667, 0.1111, 0.1556)
Operational Risks	Process Delays	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)	(0.0222, 0.0667, 0.0889)
	Resource Constraints	(0.4667, 0.6000, 0.6000)	(0.2000, 0.3334, 0.4667)	(0.3334, 0.4667, 0.6000)	(0.0667, 0.2000, 0.2666)	(0.4667, 0.6000, 0.6000)	(0.2000, 0.3334, 0.4667)
	Errors in Assessment	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)	(0.1556, 0.2000, 0.2000)	(0.1556, 0.2000, 0.2000)
Pedagogical Risks	Teaching Quality Decline	(0.3111, 0.4000, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.3111, 0.4000, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)	(0.1333, 0.2222, 0.3111)
	Programme Irrelevance	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1556, 0.2000, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)
	Student Misconduct	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.0222, 0.0667, 0.0889)

Main Criteria	Sub-Criteria	Expert1		Expert2		Expert3	
		FPIS	FNIS	FPIS	FNIS	FPIS	FNIS
Compliance & Regulatory Risks	Regulatory Non-Compliance	(0.2222, 0.3111, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.2222, 0.3111, 0.4000)	(0.1333, 0.2222, 0.3111)	(0.2222, 0.3111, 0.4000)	(0.2222, 0.3111, 0.4000)
	Policy Breaches	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.0667, 0.1111, 0.1556)	(0.1556, 0.2000, 0.2000)	(0.1111, 0.1556, 0.2000)
	Data Privacy Violations	(0.3111, 0.4000, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.3111, 0.4000, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.3111, 0.4000, 0.4000)	(0.2222, 0.3111, 0.4000)
Reputational Risks	Reputation Damage	(0.2222, 0.3111, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.2222, 0.3111, 0.4000)	(0.0444, 0.1333, 0.1778)	(0.2222, 0.3111, 0.4000)	(0.1333, 0.2222, 0.3111)
	CQI Failures	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.0667, 0.1111, 0.1556)	(0.0222, 0.0667, 0.0889)	(0.1111, 0.1556, 0.2000)	(0.1111, 0.1556, 0.2000)
	Health Crises	(0.4667, 0.6000, 0.6000)	(0.3334, 0.4667, 0.6000)	(0.4667, 0.6000, 0.6000)	(0.3334, 0.4667, 0.6000)	(0.4667, 0.6000, 0.6000)	(0.3334, 0.4667, 0.6000)

F. Step 5: Distance from FPIS and FNIS

Table 9 presents the computed distances of each alternative from the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS). For the Face-to-Face alternative, the distance from the FPIS is 1.652, while the distance from the FNIS is 0.992. The Online alternative exhibits a D+ value of 1.160 and a D- value of 1.483, whereas Hybrid Learning has corresponding distances of 1.440 (D+) and 1.210 (D-). These metrics quantify each alternative's proximity to ideal and worst-case scenarios, thereby facilitating comparative risk assessment.

Table 10 provides detailed distance calculations across each primary risk category. Under Technological Risks, Face-to-Face learning displays a D+ value of 0.371 and a D- value of 0.117, whereas Online and Hybrid Learning alternatives present D+ values of 0.162 and 0.211, respectively. Regarding Operational Risks, the Face-to-Face alternative shows the highest D+ value of 0.588 and lacks a corresponding D- value, indicating pronounced vulnerability. In contrast, Online and Hybrid Learning modes report D+ values of 0.210 and 0.287, respectively.

In Pedagogical Risks, Face-to-Face learning registers a D+ value of 0.215 and a D- value of 0.279, whereas the Online mode reveals higher vulnerability with a D+ value of 0.318 and a lower D- of 0.175. Hybrid Learning exhibits the highest D+ value in this category at 0.363, alongside a comparatively low D- value of 0.129. Under Compliance and Regulatory Risks, Face-to-Face learning demonstrates a D+ value of 0.159 and a relatively high D- value of 0.390. The Online and Hybrid alternatives report D+ values of 0.263 and 0.290, respectively. Lastly, within Reputational Risks, Face-to-Face learning records a D+ value of 0.319 and a D- value of 0.206, while the Online and Hybrid modes yield D+ values of 0.208 and 0.289, respectively.

Table 9: Distance from FPIS and FNIS for Overall

	Alternative	D+ (Best)	D- (Worst)
Overall	Face-to-Face	1.652	0.992
	Online	1.160	1.483

	Hybrid Learning	1.440	1.210

Table 10: Distance from FPIS and FNIS for Main Criteria

Main Criteria	Alternative	D+ (Best)	D- (Worst)
Technological Risks	Face-to-Face	0.371	0.117
	Online	0.162	0.328
	Hybrid Learning	0.211	0.286
Operational Risks	Face-to-Face	0.588	0.000
	Online	0.210	0.378
	Hybrid Learning	0.287	0.302
Pedagogical Risks	Face-to-Face	0.215	0.279
	Online	0.318	0.175
	Hybrid Learning	0.363	0.129
Compliance & Regulatory Risks	Face-to-Face	0.159	0.390
	Online	0.263	0.284
	Hybrid Learning	0.290	0.258
Reputational Risks	Face-to-Face	0.319	0.206
	Online	0.208	0.318
	Hybrid Learning	0.289	0.236

G. Step 6:Closeness Coefficient (CC)

Table 11 presents the calculated CC values for each learning alternative within the Overall category. The Face-to-Face alternative obtained a CC value of 0.3752, indicating relatively lower closeness to the ideal solution compared to the other alternatives. Online Learning achieved the highest CC value (0.5611), signifying its greater proximity to the ideal scenario and, therefore, suggesting its potential suitability based on the assessed risk factors. Hybrid Learning holds an intermediate position with a CC value of 0.4566, reflecting moderate performance relative to the other two alternatives.

Table 12 elaborates further by detailing Closeness Coefficients across each primary risk category, including Technological, Operational, Pedagogical, Compliance and Regulatory, and Reputational Risks. Under Technological Risks, Online Learning exhibits the highest CC value (0.6694), indicating the lowest relative risk, followed by Hybrid Learning (0.5755), and Face-to-Face (0.2398). Within Operational Risks, Online Learning again demonstrates the most favourable outcome (CC = 0.6429), whereas Hybrid Learning is moderately favourable (CC = 0.5127), and Face-to-Face Learning reveals significant vulnerability, reflected in its lowest CC value (0.0000).

In the context of Pedagogical Risks, the Face-to-Face alternative exhibits superior performance, reflected by the highest CC value (0.5648), suggesting stronger pedagogical effectiveness compared to Online Learning (CC = 0.3550) and Hybrid Learning (CC = 0.2622). Within Compliance and Regulatory Risks, Face-to-Face Learning again emerges as the most advantageous alternative (CC = 0.7104), surpassing Online Learning (CC = 0.5192) and Hybrid Learning (CC = 0.4708). Lastly, in terms of Reputational Risks, Online Learning leads with a CC value of 0.6046, followed by Hybrid Learning (0.4495), and Face-to-Face Learning demonstrating the lowest closeness coefficient (0.3924).

Example: Calculating CC for Face-to-Face (Overall)

Using values:

$$D_i^+ = 0.3324$$

$$D_i^- = 0.1996$$

$$CC = \frac{D^-}{D^+ + D^-} = \frac{0.1996}{0.3324 + 0.1996} = \frac{0.1996}{0.532} = 0.3752$$

Table 11: Closeness Coefficient (CC) for Overall

	Alternative	CC Value
Overall	Face-to-Face	0.3752
	Online	0.5611
	Hybrid Learning	0.4566

Table 12: Closeness Coefficient (CC) for Main Criteria

Main Criteria	Alternative	CC Value
Technological Risks	Face-to-Face	0.2398
	Online	0.6694
	Hybrid Learning	0.5755
Operational Risks	Face-to-Face	0.0000
	Online	0.6429
	Hybrid Learning	0.5127
Pedagogical Risks	Face-to-Face	0.5648
	Online	0.3550
	Hybrid Learning	0.2622
Compliance & Regulatory Risks	Face-to-Face	0.7104
	Online	0.5192
	Hybrid Learning	0.4708
Reputational Risks	Face-to-Face	0.3924
	Online	0.6046
	Hybrid Learning	0.4495

H. Step 7: Ranking

Table 13 provides the ranking of alternatives based on the calculated CC values. In the overall evaluation, the Online alternative attained the highest CC value (0.5611), thus achieving the first rank. Hybrid Learning secured the second position with a CC value of 0.4566, while Face-to-Face Learning ranked third, having a CC value of 0.3752. Table 14 offers a detailed breakdown of rankings across each primary risk category. Under Technological Risks, the Online alternative demonstrated superior performance, ranking first with a CC value of 0.6694. Hybrid Learning followed in second place (CC = 0.5755), with Face-to-Face positioned third (CC = 0.2398). In Operational Risks, Online Learning again secured the first rank (CC = 0.6429), Hybrid Learning occupied the second position (CC = 0.5127), and Face-to-Face ranked third, reflecting notable vulnerability (CC = 0.0000).

In the Pedagogical Risks category, Face-to-Face Learning achieved the highest CC value (0.5648), ranking first and indicating strong pedagogical effectiveness, whereas Online (CC = 0.3550) and Hybrid Learning (CC = 0.2622) were ranked second and third, respectively. Concerning Compliance and Regulatory Risks, Face-to-Face Learning maintained the top position (CC = 0.7104), with Online Learning ranked second (CC = 0.5192) and Hybrid Learning third (CC = 0.4708). Lastly, under Reputational Risks, Online Learning ranked first (CC = 0.6046), followed by Hybrid Learning in second place (CC = 0.4495), and Face-to-Face Learning ranked third (CC = 0.3924). These rankings underscore the comparative strengths and limitations of each alternative across various risk dimensions, revealing that Online Learning generally emerged as the most favourable overall, while Face-to-Face Learning excelled specifically in Pedagogical and Compliance and Regulatory aspects.

Table 13: Ranking of Overall

	Alternative	**CC Value**	**Rank**
Overall	Online	0.5611	1
	Hybrid Learning	0.4566	2
	Face-to-Face	0.3752	3

Table 14: Ranking for Main Criteria

Main Criteria	**Alternative**	**CC Value**	**Rank**
Technological Risks	Online	0.6694	1
	Hybrid Learning	0.5755	2
	Face-to-Face	0.2398	3
Operational Risks	Online	0.6429	1
	Hybrid Learning	0.5127	2
	Face-to-Face	0.0000	3
Pedagogical Risks	Face-to-Face	0.5648	1
	Online	0.3550	2
	Hybrid Learning	0.2622	3
Compliance & Regulatory Risks	Face-to-Face	0.7104	1
	Online	0.5192	2
	Hybrid Learning	0.4708	3
Reputational Risks	Online	0.6046	1
	Hybrid Learning	0.4495	2

Main Criteria	Alternative	CC Value	Rank
	Face-to-Face	0.3924	3

V. Conclusions And Future Work

The findings of this study underscore the relative effectiveness of different learning modes in addressing and mitigating risks associated with teaching evaluation processes. According to the overall rankings derived from CC analysis, the Online learning alternative emerged as the most favourable option with a CC value of 0.5611, outperforming Hybrid Learning (0.4566) and Face-to-Face Learning (0.3752). These outcomes emphasize the superior capability of Online learning environments in managing risks, particularly in technological, operational, and reputational domains, thereby benefiting educational institutions through enhanced digital resilience, streamlined operational procedures, and improved institutional image.

A detailed assessment of each primary risk criterion further reveals that Online learning achieved the highest rankings in Technological Risks (CC=0.6694), Operational Risks (CC=0.6429), and Reputational Risks (CC=0.6046). This suggests significant advantages for institutions adopting online learning, as they are better equipped to address digital infrastructure vulnerabilities, optimize workflow efficiency, and safeguard their reputation. Conversely, Face-to-Face Learning exhibited notable strengths in Pedagogical Risks (CC=0.5648) and Compliance and Regulatory Risks (CC=0.7104), highlighting its efficacy in promoting instructional quality, learner engagement, and effective compliance with educational policies and regulatory frameworks.

Hybrid Learning consistently positioned itself between the two alternatives across most criteria, reflecting its balanced but moderate risk management performance. Although it did not exhibit dominance in any single category, its integrated approach presents institutions with a strategic advantage through flexibility, allowing tailored responses to diverse educational challenges. These results offer practical benefits for educational institutions, providing a structured basis to inform strategic decisions concerning teaching methodologies, resource allocation, and risk management practices. By clearly identifying strengths and vulnerabilities within each instructional mode, institutions can better tailor their approaches to align with specific organizational priorities and stakeholder expectations.

Future research directions may involve extending the evaluation framework by incorporating additional learning alternatives, refining the weighting of evaluation criteria through expert consensus methods, and integrating real-time data analytics for more dynamic and responsive decision-making. Furthermore, investigating the potential impact of emerging technologies, such as artificial intelligence and adaptive learning systems, on risk mitigation processes could facilitate substantial advancements in teaching evaluation practices, ultimately enhancing institutional resilience and educational quality.

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