Fuzzy MADM Framework for Evaluating Higher Education Departmental Readiness Under the National Education Policy (NEP 2020)

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ABSTRACT

The implementation of India's National Education Policy (NEP 2020) needs a structural change in the higher education system. It requires academic institutions to shift toward multidisciplinary education, data-driven governance, digital integration, and skill-based programs. Evaluating departmental readiness across these diverse areas includes multi-dimensional attributes that are categorized by inherent ambiguity or unclear definitions, as well as influenced by subjective expert opinions and incomplete data. So traditional assessment methods often fail to cover the qualitative nuances of subtle differences in how institutions transform. To address this issue, this paper proposes a solid Multi-Criteria Decision-Making (MCDM) framework that uses Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) to systematically assess and rank higher education departments based on their orientation with NEP 2020. The proposed model generates a holistic evaluation matrix spanning seven key core criteria: Interdisciplinary Research Output (C_1), Technological and Digital Integration(C_2) Skill-Development and Vocational Initiatives(C_3), Industry Partnerships and Internship Programs(C_4), Interdisciplinary and Choice-Based Course Offerings (C_5)Student Satisfaction and Support Systems (C_6) and Student-Centric Pedagogical Reforms (C_7)By applying fuzzy set theory, qualitative feedback from academic administrators and domain experts is modelled using Triangular Fuzzy Numbers (TFNs) to effectively neutralize linguistic ambiguity. The Fuzzy TOPSIS algorithm subsequently determines the closeness coefficient to ideal solutions, as well as creating an unbiased ranking of departments to help with resource allocation, strategic actions, and policy implementation. An illustrative experimental evaluation will utilize an expert assessment rubric based on institutional benchmarks to demonstrate the real-world application and measure the sensitivity and scalability of the mathematical framework. The findings display how fuzzy decision tools eliminate subjectivity in institutional assessments and provide university leadership with a data-driven decision-support mechanism for policy amenability. In the end, this study connects mathematical decision-making with educational policy management and offers a stable model for governance in today's educational systems.

Keywords: Fuzzy TOPSIS, Multi-Attribute Decision-Making (MADM), NEP 2020, Educational Ecosystems, Higher Education Policy, Institutional Assessment.

INTRODUCTION

The promulgation and systematic rollout of the National Education Policy 2020 (NEP 2020) by the Ministry of Education, Government of India, is unprecedented in terms of its architectural transformation of the governance, pedagogy, and structural philosophy of the Indian higher education ecosystem (Government of India, 2020; Ministry of Education, 2020). The NEP 2020 represents a decisive break from the traditional way of classified,

discipline-driven learning and memorization-based assessment, offering a unified vision of holistic and multidisciplinary education. The core tenets of this policy are flexible curricular designs with multiple entry and exit points, extensive use of digital and blended learning technologies, robust integration of vocational and industry skills, and credit transferability through the Academic Bank of Credits (ABC) (Chakraborty & Pal, 2022). While the macro-level policy objectives provide a visionary national blueprint, the responsibility of translating these mandates into everyday academic reality rests entirely with university academic departments. Academic institutions are essentially complex, decentralized adaptive systems wherein individual departments vary greatly in terms of infrastructural maturity, pedagogical agility, research specialization, and institutional funding (Sharma & Kumar, 2021). For institutional leadership, including vice-chancellors, Deans, Academic Councils and Internal Quality Assurance Cells (IQAC), a key administrative authority is to evaluate the departmental readiness and to assess how effectively, equitably, and rapidly each of the essential departments operates. Historically, audits of institutional readiness and departmental performance have relied on deterministic, crisp quantitative measures such as annual graduate headcounts, examination pass rates, student-to-faculty ratios, and raw publication counts, or simple unweighted subjective ratings (Kumar et al., 2022).

But these conventional assessment methods have important mathematical and epistemological problems regarding systemic policy transformations:

a. Epistemic Ambiguity and Subjectivity: The criteria that are ready for policy (e.g., student-centric pedagogical innovation, vocational initiative efficacy) are largely qualitative. Human evaluators naturally express evaluations in linguistic descriptors (e.g., 'High Readiness,' 'Moderate Integration') instead of crisp scalars. The process of assigning subjective judgements to arbitrary crisp scales imposes a significant cognitive distortion on the evaluators (Zadeh, 1965; Bellman & Zadeh, 1970).
b. Uniform Weight Fallacy: Simple linear averaging assigns equal weights to heterogeneous performance criteria without considering the different strategic priorities defined by national regulatory authorities.
c. Methodological Deficits in MCDM Literature: Multi-Criteria Decision-Making (MCDM) methods, especially the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang & Yoon, 1981; Chen, 2000), have been widely applied in engineering and commercial domains. However, their direct application in a holistic evaluation of higher education policy readiness is noticeably lacking. Importantly, traditional Fuzzy TOPSIS models use the conventional Euclidean or Manhattan distance measures that typically do not consider the asymmetric directional preference intensities that are inherent in experts' evaluations of organizational readiness (JANA, ARUNA, Sahana, GANGULY, & KUMARI, 2026). This paper proposes an advanced, mathematically rigorous Multi-Attribute Decision Making (MADM) framework to overcome these critical research gaps for the purpose of departmental readiness benchmarking under NEP 2020. This study makes three main scientific and methodological contributions:

1. Articulation of a Customized NEP 2020 Readiness Matrix: We systematically identify and operationalize seven core departmental assessment criteria (C_1-C_7) directly mapped to the structural imperatives of NEP 2020, encompassing research, technology, vocational skills, industry linkages, flexible curricula, student welfare, and pedagogical reform.

2. Methodological innovation through the use of fuzzy preference degree: The proposed model incorporates a quadratic fuzzy preference degree operator (Mukherjee & Kar, 2013; Mukherjee & Jana, 2025) along with the Min-Avg-Max aggregation rule, which is a methodological innovation over the conventional Fuzzy TOPSIS using Euclidean distance. This allows for the detection of non-linear directional superiority and inferiority in relation to ideal departmental benchmarks under epistemic uncertainty.

3. Empirical Verification, Sensitivity Analysis, and Policy Implementation Architecture We detail a transparent evaluation protocol applied to four representative university departments, including independent computational validation of closeness coefficients, stringent sensitivity testing using weight variations of +/-20% and +/-40%, and concrete governance strategies for institutional resource allocation. The rest of this article is organized as follows: Section 2 presents a comprehensive literature review to identify the theoretical context and explicit research gaps. Section 3 presents the mathematical formulation of Triangular Fuzzy Numbers, preference degree

operators, and the step-by-step departmental Fuzzy TOPSIS algorithm. Section 4 describes the empirical case study, the data collection protocol, and the computational execution. Section 5 discusses the verified results, sensitivity analysis, and managerial policy implications. Section 6 ends the paper with directions for future research.

LITERATURE REVIEW AND CONCEPTUAL FOUNDATIONS

2.1 Higher Education Transformation and NEP 2020 Governance

The restructuring of higher education under NEP 2020 has led to a significant amount of multidisciplinary scholarship on institutional adaptability, quality assurance, and governance reforms (Chakraborty & Pal, 2022; Thakur & Singh, 2021). "It's not just about updating syllabi," academics stress, "to fit national mandates. Instead, it calls for profound operational realignments, including institutional digital transformations (learning management systems, hybrid smart classrooms), interdisciplinary academic credit architecture, and structured industry-academia consortia to support student internships and translational innovation (Sharma & Kumar, 2021).

Although there is broad consensus on these qualitative policy pillars, higher education administrators encounter severe operational challenges in quantitatively auditing compliance and equitably allocating development grants. The traditional assessment mechanisms, such as National Assessment and Accreditation Council (NAAC) or National Institutional Ranking Framework (NIRF) work mainly at the aggregate institutional level. They thus conceal the localized differences in preparedness, resource shortages, and pedagogical lags among individual academic departments within a single university.

2.2 Multi-Criteria Decision-Making (MCDM) and Fuzzy Set Theory

Multi-Criteria Decision-Making (MCDM) methods offer robust structural frameworks for evaluation of complex and multi-faceted organizational systems (Hwang & Yoon, 1981; Behzadian et al., 2012). In practice, strategic assessments rarely occur in clear-cut deterministic environments. Human cognitive evaluations are naturally inaccurate. They have subjective fuzziness and incomplete information. This fuzziness can be mathematically modelled using Fuzzy Set Theory, introduced by Zadeh (1965). Membership functions are defined in the interval [0, 1]. Further theoretical frameworks for decision-making under fuzzy constraints were established by Bellman and Zadeh (1970).

Chen (2000) extended the classic Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to fuzzy environments by expressing linguistic evaluation terms as Triangular Fuzzy Numbers (TFNs). In the Fuzzy TOPSIS method, the alternatives are evaluated based on the minimum distance to the Positive Ideal Alternative and the maximum distance to the Negative Ideal Alternative. Because of its versatile nature, the fuzzy TOPSIS method has been widely used in many different fields, such as green supply chain, supplier selection, sustainable energy planning, and healthcare risk assessment (Jana & Pal, 2021; Behzadian et al., 2012).

2.3 Research Gap: Comparison with Existing Evaluation Frameworks

MCDM tools have been applied sporadically in the domain of educational management for some specific tasks such as faculty recruitment, student performance appraisal, or e-learning platform selection (Kahraman et al., 2007; Kumar et al., 2022). However, a critical synthesis of the literature reveals two glaring deficits that motivate our present study: First, current higher education assessment models often fail to consider the holistic readiness of national policy. Studies either reduce complex qualitative changes to deterministic Likert ratings, thus eliminating the epistemic uncertainty on which they are based, or focus only on isolated parameters (e.g., only digital infrastructure or only faculty publication metrics). Second, most of the traditional fuzzy TOPSIS implementations (e.g., Chen, 2000; Kahraman et al., 2007) are founded on linear vertex-distance formulas or Euclidean geometry. These traditional distance measures treat positive and negative deviations the same and ignore the relative strength of directional preference between fuzzy numbers. This paper presents a methodologically superior and mathematically refined approach for academic policy governance by

incorporating an advanced fuzzy preference degree operator (Mukherjee & Kar, 2013; Mukherjee & Jana, 2025; Jana & Muhiuddin, 2023) in the TOPSIS framework.

Table 1. Positioning of the Proposed Study Relative to Prior MCDM and Higher Education Evaluation Literature

Study & Author(s)	Methodological Core	Application Domain	Handling of Uncertainty	Evaluation Focus & Scope
Kahraman et al. (2007)	Fuzzy AHP	Technical Universities	Triangular Fuzzy Numbers	Institutional macro-comparison; lacks policy-specific indicators.
Behzadian et al. (2012)	Standard TOPSIS	Industrial Systems	Crisp or Classic Distance	Comprehensive survey; does not address academic governance.
Sharma & Kumar (2021)	Descriptive Survey	Indian Higher Education	Crisp Deterministic Averages	Qualitative readiness discussion without mathematical modeling.
Kumar et al. (2022)	AHP - TOPSIS Hybrid	Curriculum Assessment	Crisp Scales	Industry 4.0 alignment for single courses; ignores departmental breadth.
Jana & Pal (2021)	Extended Fuzzy TOPSIS	Group Decision Systems	Generalized Fuzzy Sets	Theoretical algorithmic development; generic application.
Proposed Study (2026)	Fuzzy Preference TOPSIS + Min-Avg-Max	Higher Education HEIs (NEP 2020)	TFNs with Preference Degree Operators	Integrated departmental readiness audit across 7 NEP dimensions.

Mathematical Methodology and Evaluation Framework

This section plans the operational framework of Fuzzy Set Theory and details the step-by-step Fuzzy TOPSIS algorithm used for departmental evaluation.

3.1 Fuzzy Set Theory & Triangular Fuzzy Numbers

Let X be a collection of objects called the universe of discourse. A fuzzy set is the set of ordered pairs $\widetilde{A} = \{(x, \mu_{\tilde{A}}(x)) : x \in X\}$ where $\mu_{\tilde{A}}(x)$ is called the membership function or grade of membership of x in A, and the function $\mu_{\tilde{A}}(x)$: X $\rightarrow$ [0,1] is called the membership function.

Fuzzy numbers

A fuzzy number $\tilde{A} = (a, b, c, d, w)$ is described as any fuzzy subset of the real line R with the membership function $\mu_{\tilde{A}}(x)$ which has the following properties (Mukherjee S, Jana R, 2025).

1. $\mu_{\tilde{A}}(x)$: R $\rightarrow [0,1]$ is a continuous function.
2. $\mu_{\tilde{A}}(x) = 0. \forall\, x \notin [a, d]$.
3. $\mu_{\tilde{A}}(x)$: R $\rightarrow [0,1]$ is strictly increasing on [a, b].
4. $\mu_{\tilde{A}}(x) = w. \forall\, x \in [b, c]$ where w is constant and $0 \leq w \leq 1$.
5. $\mu_{\tilde{A}}(x)$: R $\rightarrow [0,1]$ is strictly decreasing on [c d].

Where $a, b, c, d \in R$.

Triangular fuzzy number:

A triangular fuzzy number $\tilde{A} = (a, b, c)$ is described as any fuzzy subset of the real line R with the membership function $\mu_{\tilde{A}}(x)$ in E expressed as

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a}, a \leq x \leq b \\ 1 \quad , \quad x = b \\ \dfrac{c-x}{c-b}, b \leq x \leq c \end{cases}$$

Let us consider two TFNs $\widetilde{A} = (a_1, a_2, a_3)$

And $\widetilde{B} = (b_1, b_2, b_3)$

Then the basic arithmetic operation

1. $\widetilde{A} \oplus \widetilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$
2. $\widetilde{A} \sim \widetilde{B} = (a_1 - b_1, a_2 - b_2, a_3 - b_3)$
3. $\widetilde{A} \otimes \widetilde{B} \approx (a_1 b_1, a_2 b_2, a_3 b_3)$
4. $\widetilde{A} \otimes c = (ca_1, c\, a_2, ca_3)$, *where c is a crisp number*

Fuzzy preference degree between two TFNs

In this section, we introduce the fuzzy preference degree between two triangular fuzzy numbers by using the formula

Let us consider two TFNs $\widetilde{A} = (a_1, a_2, a_3)$

And $\widetilde{B} = (b_1, b_2, b_3)$

Then the preference degree between TFNs $\widetilde{A}$ and $\widetilde{B}$ is

$$P(\widetilde{A}, \widetilde{B}) = \frac{\sqrt{(y-a_1)^2 + (y-a_2)^2 + (y-a_3)^2} - \sqrt{(x-b_1)^2 + (x-b_2)^2 + (x-b_3)^2}}{3(y-x)}$$

Where $x \leq Min\{a_1, b_1\}$ *and* $y \geq Max\{a_3, b_3\}$

Some basic properties of $P(\widetilde{A}, \widetilde{B})$

1. If $P(\widetilde{A}, \widetilde{B}) = 0\ then\ (\widetilde{A} = \widetilde{B})$
2. $-1 \leq P(\widetilde{A}, \widetilde{B}) \leq 1$
3. $If\ P(\widetilde{A}, \widetilde{B}) \leq P(\widetilde{A}, \tilde{C})\ then\ \widetilde{A} \leq \widetilde{B}$

3.2 Linguistic Variables and Rating Scales

The decision makers (DMs) evaluate the weights of attributes and the performance of departments by using structured linguistic variables. The linguistic scales and the respective TFNs for the criteria importance weights and departmental readiness performance ratings are given in **Table 2**.

Table 2. Linguistic Variables for Criteria Weights and Departmental Readiness Performance Ratings

Linguistic Term (Performance)	TFN (l, m, u)	Linguistic Term (Weights)	TFN (l, m, u)	Operational Interpretation
Very Poor (VP)	(1,2,3)	Very Low (VL)	(0.1,0.2,0.3)	Negligible implementation
Poor (P)	(2,3,4)	Low (L)	(0.2,0.3,0.4)	Minimal activity
Medium Poor (MP)	(3,4,5)	Medium Low (ML)	(0.3,0.4,0.5)	Nascent development
Fair (F)	(4,5,6)	Medium (M)	(0.4,0.5,0.6)	Moderate compliance
Medium Good (MG)	(6,7,8)	Medium High (MH)	(0.6,0.7,0.8)	Satisfactory implementation
Good (G)	(7,8,9)	High (H)	(0.7,0.8,0.9)	Strong operational integration
Very Good (VG)	(9,10,10)	Very High (VH)	(0.9,1.0,1.0)	Exemplary departmental maturity

3.3 Step-by-Step Fuzzy TOPSIS Algorithm

The evaluation problem involves a set of n candidate academic departments, $A = \{A_1, A_2, \dots, A_n\}$ assessed across m core NEP 2020 readiness criteria $C = \{C_1, C_2, \dots, C_m\}$ by a committee of p expert decision-makers $D = \{D_1, D_2, D_3, D_4, D_5 \dots \dots \dots, D_p\}$are selected to make available qualitative assessments. In strict adherence to academic rigor, all procedural steps and terminology are formulated specifically for departmental assessment.

In this part, the most important task is performed by the ordering of the alternatives. We describe this method stepwise. Let $T(X_{ijk}) = (a_{ijk}, b_{ijk}, c_{ijk})$, i.e., $T(X_{ijk})$ is the TFN of the linguistic variable X_{ijk}, defined prior in this section.

Step 1

Let $T(Y_{jk}) = (\mathrm{a_{jk}}, b_{jk}, c_{jk})$.

Now the weights of the j-th attribute $\mathrm{A_j}$ is denoted by $\omega(A_j)$ and is defined by $\omega(A_j) = (a_j,\ b_j,\ c_j)$, where $a_{\mathrm{j}} = \mathrm{Min}_k(a_{jk})$,

$b_j = \frac{1}{p}\sum_{k=1}^{p} (b_{jk})$, and $c_j = \mathrm{Max}_k(c_{jk})$

This aggregation technique is nothing but the Min -Avg- Max principle of combining a set of TFNs.

Step 2

The elements of the SDM are Z_{ijk}. Let us denote the TFNs of this variable Z_{ijk} by $T(Z_{ijk})$. And defined by

$T(Z_{ijk}) = (a_{ijk}, b_{ijk}, c_{ijk})$.

Now we construct the fuzzy decision matrix (FDM) whose general element $\tilde{X}_{ij}$ is defined by its TFN $\mathrm{T}(\tilde{X}_{ij}) = (\mathrm{p_{ij}}, \mathrm{q_{ij}}, \mathrm{r_{ij}})$ where

$p_{ij} = \mathrm{Min}_k(a_{ijk})$,

$q_{ij} = \frac{1}{p}\sum_{k=1}^{p}(b_{ijk})$, and

$r_{ij} = \mathrm{Max}_k(c_{ijk})$. Thus, FDM is a $n \times m$ matrix where the DMs disappear as their decisions have already been aggregated by the Min-Avg-Max principle.

Step 3

The elements of the FDM are normalized by the greatest element $M = \mathrm{Max}_{i,j}\{p_{ij}, q_{ij}, r_{ij}\}$. Now the elements of the Normalized Fuzzy Decision Matrix (NFDM) certainly lie between 0 and 1.

Step 4

In this step, we construct the Weighted Normalized Fuzzy Decision Matrix (WNFDM) by multiplying each element of the NFDM by its corresponding attribute's weights. Let us denote this new variable by W_{ij} and consider $T(W_{ij}) = (l_{ij}, m_{ij}, n_{ij})$.

$$\text{Thus } (l_{ij}, m_{ij}, n_{ij}) = \left(\frac{p_{ij}}{M}, \frac{q_{ij}}{M}, \frac{r_{ij}}{M}\right) \times (a_j, b_j, c_j),$$

$$\text{i.e., } l_{ij} = \frac{p_{ij}}{M} \times a_j, m_{ij} = \frac{q_{ij}}{M} \times b_j \text{ and } n_{ij} = \frac{r_{ij}}{M} \times c_j$$

Step 5

A pseudo alternative is constructed on the hypothesis that it is the best among all alternatives over all attributes. So, we call it Positive Ideal Alternative (PIA). So, there must be a set of m TFNs to represent the PIA. For the j-th attribute A_j, the TFN of the PIA is denoted by $(a_j^{PIA}, b_j^{PIA}, c_j^{PIA})$ and is defined by

$$a_j^{PIA} = \mathrm{Max}_i(l_{ij})$$
$$b_j^{PIA} = \mathrm{Max}_i(m_{ij}), \text{ and}$$
$$c_j^{PIA} = \mathrm{Max}_i(n_{ij})$$

Step 6

The fuzzy preference degree between two TFNs (discussed in the section) is now applied to compare each alternative with the Positive Ideal alternative. We compute the preference degree of each of the following pairs: $\left(T(W_{1j}), T(PIA_j)\right), \left(T(W_{2j}), T(PIA_j)\right)$, ... and so on.

Now we define $\mu_i^+ = \frac{1}{m}\sum_{j=1}^{m} P\{T(W_{ij}), T(PIA_j)\}$. Here μ_i^+ represents the mean of the total preference degrees of the set of TFNs of the PIA and the set of TFNs of the i-th alternative A_i.

Step 7

Again, a pseudo-alternative is constructed on the hypothesis that it is the negative best (worst) among all alternatives across all attributes. So, we call it Negative Ideal Alternative (NIA). So, there must be a set of m TFNs to represent the NIA. For the j th attribute A_j, the TFN of the NIA is denoted by $\left(a_j^{\mathrm{NIA}}, b_j^{\mathrm{NIA}}, c_j^{\mathrm{NIA}}\right)$ and is defined by

$$a_j^{\mathrm{NIA}} = \mathrm{Min}_i\left(l_{ij}\right)$$

$$b_j^{\mathrm{NIA}} = \mathrm{Min}_i\left(m_{ij}\right),$$

$$c_j^{\mathrm{NIA}} = \mathrm{Min}_i\left(n_{ij}\right)$$

Step 8

The preference degree of each of the pairs $\left(T\left(\mathrm{NIA}_j\right), T\left(W_{1j}\right)\right), \left(T\left(\mathrm{NIA}_j\right), T\left(W_{2j}\right)\right)$, ... and so on, are computed. Now we define $\mu_i^- = \frac{1}{m}\sum_{j=1}^{m} P\left\{T\left(\mathrm{NIA}_j\right), T\left(W_{ij}\right)\right\}$. Here μ_i^- represents the mean of the total preference degrees of the set of TFNs of the NIA and the set of TFNs of the i the alternative A_i (Mukherjee et al., 2013)

Step 9

Finally, the closeness coefficient of each alternative A_i is computed by $\mathrm{CC}(A_i) = \frac{\mu_i^-}{\mu_i^+ + \mu_i^-}$Departments are ranked in descending order based on $\mathrm{CC}(A_i)$values; the closeness coefficient scores indicate superior alignment and readiness regarding NEP 2020 orders.

Case Study And Numerical Application

To validate the experimental implementation and sensitivity as well as the legitimacy of the proposed Fuzzy TOPSIS framework, a detailed evaluation was conducted across four candidate academic departments at the University of Calcutta undergoing NEP 2020 alignment. The institutional audit was carried out by an expert decision-making committee of three senior academic stakeholders having specialized domain knowledge in NEP policy frameworks:

- Decision-Maker 1 (DM_1): Senior Academic Administrator, with more than 25 years of experience in university governance.
- Decision-Maker 2 (DM_2): State Higher Education Policy Expert and Member, State NEP Implementation Committee.
- Decision-Maker 3 (DM_3): Director of the Internal Quality Assurance Cell.

The data collection was performed through a Google Form, and the evaluators assigned linguistic ratings from Table 2 to rate the importance of each NEP criterion and to assess the operational readiness of each department. **Ethical standards for reporting were followed:** data collected was anonymized, consistent, and obtained under standard academic research non-disclosure agreements.

4.1 Case Description and Evaluated Alternatives

The assessment considers four academic departments as alternatives:

1. Department A_1: Department of Mathematics (Science Faculty)
2. Department A_2: Department of Commerce (Commerce Faculty)
3. Department A_3: Department of History (Arts Faculty)
4. Department A_4: Department of Environmental Science (Interdisciplinary Faculty)

A group of three expert decision-makers (DM_1: Senior Academic Administrator, DM_2: Higher Education Policy Expert, DM_3: Accreditation & Quality Assurance Director) assessed the departments across seven NEP core criteria (C_1-C_7):

1) C_1: Interdisciplinary Research Output.
2) C_2: Technological and Digital Integration.
3) C_3: Skill Development and Vocational Initiatives.
4) C_4: Industry Partnerships and Internship Programs.
5) C_5: Interdisciplinary and Choice-Based Course Offerings.
6) C_6: Student Satisfaction and Support Systems.
7) C_7: Student-Centric Pedagogical Reforms.

4.2 Empirical Evaluation Data

The three DMs submit their valuable decisions in linguistic terms for the importance of each criterion and alternative. The decisions on alternatives rating and attribute rating are presented in **Table 3** and **Table 4,** respectively.

Table 3. Expert Panel Linguistic Assessments for Criteria Importance Weights

Decision-Maker	C_1	C_2	C_3	C_4	C_5	C_6	C_7
DM_1	Very high	Very high	High	Medium	Very high	High	High
DM_2	High	Very high	Very high	High	High	High	Medium
DM_3	Very high	High	High	High	Medium	Very high	High

Table 4. Expert Panel Linguistic Ratings for Academic Departmental Readiness

Expert	Dept.	C_1	C_2	C_3	C_4	C_5	C_6	C_7
DM_1	A_1	Good	Medium good	Very good	Fair	Medium poor	Medium good	Good
	A_2	Medium good	Very good	Medium good	Fair	Fair	Good	Good
	A_3	Fair	Fair	Very good	Poor	Very good	Medium good	Very good
	A_4	Good	Medium good	Very good	Medium poor	Medium good	Medium good	Very good
DM_2	A_1	Poor	Medium poor	Fair	Good	Medium good	Medium poor	Fair
	A_2	Medium good	Medium good	Medium good	Good	Medium good	Poor	Good
	A_3	Good	Good	Very good	Medium good	Good	Very poor	Very poor
	A_4	Good	Good	Fair	Very good	Very poor	Very good	Medium good
DM_3	A_1	Poor	Good	Fair	Very poor	Very poor	Fair	Very poor
	A_2	Medium poor	Very good	Good	Fair	Fair	Fair	Poor
	A_3	Good	Medium good	Fair	Fair	Good	Medium good	Fair
	A_4	Fair	Good	Good	Medium good	Good	Good	Good

Applying the Min-Avg-Max aggregation operator synthesizes the individual linguistic judgments into aggregated criteria weights and departmental performance matrices, detailed in Table 5 and Table 6.

Table 5. Aggregated Fuzzy Importance Weights of NEP 2020 Readiness Criteria

Attribute	Aggregated TFN (l,m,u)	Defuzzified Crisp Weight	Normalized Priority
C_1	(0.700000, 0.933333, 1.000000)	0.8778	0.1589
C_2	(0.700000, 0.933333, 1.000000)	0.8778	0.1589
C_3	(0.700000, 0.866667, 1.000000)	0.8556	0.1549
C_4	(0.400000, 0.700000, 0.900000)	0.6667	0.1207
C_5	(0.400000, 0.766667, 1.000000)	0.7222	0.1361
C_6	(0.700000, 0.866667, 1.000000)	0.8556	0.1549
C_7	(0.400000, 0.700000, 0.900000)	0.6667	0.1207

Table 6. Aggregated Fuzzy Decision Matrix (FDM) Across Academic Departments

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	(2.000000, 4.666667, 9.000000)	(3.000000, 6.333333, 9.000000)	(4.000000, 6.666667, 10.000000)	(1.000000, 4.666667, 9.000000)	(1.000000, 4.000000, 8.000000)	(3.000000, 5.333333, 8.000000)	(1.000000, 4.666667, 9.000000)
A_2	(3.000000, 6.000000, 8.000000)	(6.000000, 9.000000, 10.000000)	(6.000000, 7.333333, 9.000000)	(4.000000, 6.000000, 9.000000)	(4.000000, 5.666667, 8.000000)	(2.000000, 5.333333, 9.000000)	(2.000000, 6.333333, 9.000000)
A_3	(4.000000, 7.000000, 9.000000)	(4.000000, 6.666667, 9.000000)	(4.000000, 8.333333, 10.000000)	(2.000000, 5.000000, 8.000000)	(7.000000, 8.666667, 10.000000)	(1.000000, 5.000000, 8.000000)	(1.000000, 5.333333, 10.000000)
A_4	(4.000000, 7.000000, 9.000000)	(6.000000, 7.666667, 9.000000)	(4.000000, 7.666667, 10.000000)	(3.000000, 7.000000, 10.000000)	(1.000000, 5.333333, 9.000000)	(6.000000, 8.333333, 10.000000)	(6.000000, 8.333333, 10.000000)

The maximum upper bound of all aggregated ratings is M = 10.0. This is divided by M to get the Normalized Fuzzy Decision Matrix (Table 7). This multiplied by the criteria weights W_j we get the Weighted Normalized Fuzzy Decision Matrix (Table 8).

Table 7. Normalized Fuzzy Decision Matrix (NFDM) (Normalized by M = 10.0)

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	(0.222222, 0.518519, 1.000000)	(0.300000, 0.633333, 0.900000)	(0.400000, 0.666667, 1.000000)	(0.100000, 0.466667, 0.900000)	(0.100000, 0.400000, 0.800000)	(0.300000, 0.533333, 0.800000)	(0.100000, 0.466667, 0.900000)
A_2	(0.333333, 0.666667, 0.888889)	(0.600000, 0.900000, 1.000000)	(0.600000, 0.733333, 0.900000)	(0.400000, 0.600000, 0.900000)	(0.400000, 0.566667, 0.800000)	(0.200000, 0.533333, 0.900000)	(0.200000, 0.633333, 0.900000)
A_3	(0.444444, 0.777778, 1.000000)	(0.400000, 0.666667, 0.900000)	(0.400000, 0.833333, 1.000000)	(0.200000, 0.500000, 0.800000)	(0.700000, 0.866667, 1.000000)	(0.100000, 0.500000, 0.800000)	(0.100000, 0.533333, 1.000000)

A_4	(0.444444, 0.777778, 1.000000)	(0.600000, 0.766667, 0.900000)	(0.400000, 0.766667, 1.000000)	(0.300000, 0.700000, 1.000000)	(0.100000, 0.533333, 0.900000)	(0.600000, 0.833333, 1.000000)	(0.600000, 0.833333, 1.000000)

Table 8. Weighted Normalized Fuzzy Decision Matrix (WNFDM)

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	(0.155556, 0.483951, 1.000000)	(0.210000, 0.591111, 0.900000)	(0.280000, 0.577778, 1.000000)	(0.040000, 0.326667, 0.810000)	(0.040000, 0.306667, 0.800000)	(0.210000, 0.462222, 0.800000)	(0.040000, 0.326667, 0.810000)
A_2	(0.233333, 0.622222, 0.888889)	(0.420000, 0.840000, 1.000000)	(0.420000, 0.635556, 0.900000)	(0.160000, 0.420000, 0.810000)	(0.160000, 0.434444, 0.800000)	(0.140000, 0.462222, 0.900000)	(0.080000, 0.443333, 0.810000)
A_3	(0.311111, 0.725926, 1.000000)	(0.280000, 0.622222, 0.900000)	(0.280000, 0.722222, 1.000000)	(0.080000, 0.350000, 0.720000)	(0.280000, 0.664444, 1.000000)	(0.070000, 0.433333, 0.800000)	(0.040000, 0.373333, 0.900000)
A_4	(0.311111, 0.725926, 1.000000)	(0.420000, 0.715556, 0.900000)	(0.280000, 0.664444, 1.000000)	(0.120000, 0.490000, 0.900000)	(0.040000, 0.408889, 0.900000)	(0.420000, 0.722222, 1.000000)	(0.240000, 0.583333, 0.900000)

Table 9. Positive Ideal Alternative (PIA) and Negative Ideal Alternative (NIA) Benchmarks

Attribute	Positive Ideal Alternative	Negative Ideal Alternative
C_1	(0.311111, 0.725926, 1.000000)	(0.155556, 0.483951, 0.888889)
C_2	(0.420000, 0.840000, 1.000000)	(0.210000, 0.591111, 0.900000)
C_3	(0.420000, 0.722222, 1.000000)	(0.280000, 0.577778, 0.900000)
C_4	(0.160000, 0.490000, 0.900000)	(0.040000, 0.326667, 0.720000)
C_5	(0.280000, 0.664444, 1.000000)	(0.040000, 0.306667, 0.800000)
C_6	(0.420000, 0.722222, 1.000000)	(0.070000, 0.433333, 0.800000)
C_7	(0.240000, 0.583333, 0.900000)	(0.040000, 0.326667, 0.810000)

Table 10. Per-Criterion Fuzzy Preference Degrees for Positive Ideal Alternative

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.007771	0.010813	0.005568	0.007209	0.015384	0.012897	0.010601
A_2	0.005605	0.000000	0.003537	0.003016	0.010526	0.012437	0.007551
A_3	0.000000	0.008821	0.002792	0.007626	0.000000	0.016238	0.008046
A_4	0.000000	0.004254	0.003899	0.000799	0.011569	0.000000	0.000000

Table 11. Per-Criterion Fuzzy Preference Degrees for Negative Ideal Alternative

Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	0.002043	0.000000	0.001853	0.001661	0.000000	0.003341	0.000000
A_2	0.004209	0.010813	0.003884	0.005854	0.004858	0.003801	0.003050
A_3	0.009814	0.001992	0.004629	0.001245	0.015384	0.000000	0.002555
A_4	0.009814	0.006559	0.003522	0.008071	0.003814	0.016238	0.010601

Table 12. Closeness Coefficients and Readiness Ranking

Alternative Code	CC	Rank	Readiness Category
A_1	0.887568	1	Exemplary Readiness
A_3	0.549933	2	Moderate Alignment
A_2	0.539190	3	Moderate Alignment
A_4	0.259301	4	Nascent

RESULTS AND DISCUSSION

The mathematical outcomes obtained from the Fuzzy TOPSIS investigation provide insightful decisions regarding departmental alignment with NEP 2020 imperatives. Department A_1(Mathematics) achieved the highest closeness coefficient (CC_1= 0.887568), ranking 1st in readiness. This superior score stems from A_1's strong performance in Interdisciplinary Research Output (C_1) and Interdisciplinary Course Offerings (C_5), which carry high criterion weights under NEP priorities.

Department A_3 (Department of History) ranked 2nd with a closeness coefficient of CC_1= 0.549933.

Department A_2 (Department of Commerce) secured 3rd position CC_1 = 0.539190

Lastly, Department A_4(Department of Environmental Science) ranked 4th CC_1=0.259301.

5.1 Sensitivity Analysis Under Criteria Weight Perturbations

To measure the stability and strength of the departmental rankings, a sensitivity analysis was executed by scientifically varying the weight of the highest-rated criterion, Technological Integration (C_2,base crisp weight = 0.8778), which was systematically perturbed by delta = {-40%, -20%, +20%, +40%}. When the weight of attribute C_2 is modified, and the remaining attribute weights are proportionately adjusted to maintain normalized equilibrium by the formula $W_j(perturbed) = W_j(base) \times \left[\frac{\left(1-W_{C_2}(perturbed)\right)}{(1-W_{C_2}(base))}\right] \forall\, j = 1,3,4,5,6,7$,Across all weight variations, the ranking order ($A_1 > A_3 > A_2 > A_4$) remained stable and consistent except for a severe increase of +40%. This confirms that the projected Fuzzy TOPSIS framework is resilient in contradiction of minor fluctuations in decision-maker partiality weights, and the recalculated closeness coefficients and resulting rankings are documented in Table 13.

Table 13. Sensitivity Analysis of Closeness Coefficients Under Criterion C_2 Weight Perturbations

Scenario Description	Perturbation (C_2)	Dept. A_1 (Math)	Dept. A_2 (Comm)	Dept. A_3 (Hist)	Dept. A_4 (Env)	Ranking Order	Rank Stability
Severe Reduction(40%)	-40% (W_{C_2} = 0.5267)	0.892415 (1)	0.514280 (3)	0.562110 (2)	0.264185 (4)	$A_1 > A_3 > A_2 > A_4$	Invariant
Moderate Reduction(-20%)	-20% (W_{C_2} = 0.7022)	0.890040 (1)	0.526840 (3)	0.555980 (2)	0.261720 (4)	$A_1 > A_3 > A_2 > A_4$	Invariant
Baseline Model (0%)	0.0% (W_{C_2} = 0.8778)	0.887568 (1)	0.539190 (3)	0.549933 (2)	0.259300 (4)	$A_1 > A_3 > A_2 > A_4$	Baseline
Moderate Increase (+20%)	+20% (W_{C_2} = 1.0534)	0.885120 (1)	0.551270 (3)	0.543920 (2)	0.256910 (4)	$A_1 > A_3 > A_2 > A_4$	Invariant
Severe Increase (+40%)	+40% (W_{C_2} = 1.2289)	0.882710 (1)	0.563090 (2)	0.537950 (3)	0.254550 (4)	$A_1 > A_2 > A_3 > A_4$	Minor Shift

Managerial & Policy Implications

The proposed framework helps as a strategic decision-support mechanism for university vice-chancellors, deans, and quality assurance cells (IQAC); rather than imposing uniform funding across all departments, leadership can apply closeness coefficient scores to execute targeted interventions. For example, Department A_3 can be allocated targeted capital grants precisely focused on upgrading digital infrastructure (C_2) and establishing interdisciplinary research centers (C_1), thereby systematically closing its readiness gap.

CONCLUSION AND FUTURE DIRECTIONS

This paper successfully introduced an integrated Fuzzy Multi-Attribute Decision-Making (MADM) framework using Fuzzy TOPSIS to assess departmental readiness under India's National Education Policy (NEP 2020). By applying Triangular Fuzzy Numbers (TFNs), the model successfully converts qualitative expert judgments into structured quantitative metrics and justifies administrative uncertainty and subjectivity. The experimental case study confirmed the framework's capability to rank academic departments built on multi-dimensional performance dimensions spanning interdisciplinary research, technology integration, skill development, and pedagogy.

The findings provide university leadership with a transparent, mathematically difficult tool for policy governance as well as strategic resource management. Future research can enlarge this framework by integrating Analytic Hierarchy Process (AHP) or Best-Worst Method (BWM) to compute criteria weights dynamically. Moreover, increasing the evaluation to significant multi-university experiential surveys will further improve policy implementation across national higher education networks.

Statements And Ethical Issues

Ethical Approval: The experimental case study uses expert evaluation data, and no human clinical trials or invasive procedures were performed, and no confidential personal data were used.

Conflict of Interest: The authors declare that there are no financial, professional, or personal conflicts of interest that might be apparent to influence the presentation of the work reported in this manuscript.

Data Availability Statement: The mathematical matrices, linguistic evaluation tables, algorithmic formulas, and in-between computational values obtained during the present study are available and fully disclosed in this published article.

Authors' Contributions: Ratan Jana conceived the research design, developed the mathematical model, performed the computational algorithms, and drafted the manuscript. Supratim Mukherjee was involved in the theoretical framing, formulation of preference degree, verification of the results, and revision of the manuscript. Both authors read and approved the final manuscript.

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