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FAIM: Fuzzy-Neutrosophic Academic Integrity Model for University Students

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Abstract: The FAIM (Fuzzy-Neutrosophic Academic Integrity Model) is a novel approach developed to assess academic integrity among university students under conditions of uncertainty. This model emerged as a response to the challenges posed by the sudden shift from face-to-face to virtual education during the COVID-19 pandemic. This environment saw a notable increase in dishonest academic behavior. FAIM integrates fuzzy logic and neutrosophic reasoning to capture the complexity and indeterminacy of students' conduct. Key variables associated with academic dishonesty—motivation, justification, and opportunities—were examined across three simulated scenarios. The results validated FAIM's capacity to differentiate integrity levels within the student population effectively. Unlike traditional models, FAIM adapts to ambiguous behavioral patterns and provides nuanced insights. It represents a valuable decision-support tool for academic institutions aiming to promote ethical conduct. This research highlights how hybrid intelligent models can redefine integrity assessment in higher education.

Keywords: Academic Integrity. Fuzzy Logic, Neutrosophy, Assessment Under Uncertainty, Virtual Education, Student Dishonest Behavior

1. Introduction

The promotion of academic integrity remains a fundamental requirement in higher education; however, the transition to virtual learning during the COVID-19 pandemic exposed significant weaknesses in monitoring mechanisms and contributed to an increase in dishonest behaviors. The ambiguity inherent in digital environments, combined with the subjective nature of ethical considerations, complicates the accurate assessment of academic integrity. In this context, there is a pressing need for models capable of addressing complexity and uncertainty. To respond to this challenge, the FAIM (Fuzzy-Neutrosophic Academic Integrity Model) was proposed as a hybrid approach that incorporates factors such as motivation, opportunity, and justification for misconduct, aiming not only to measure academic integrity but also to promote ethical behavior within higher education institutions.

In continuation of this discussion, academic dishonesty emerges as a critical ethical concern, particularly in virtual educational settings where traditional oversight is diminished. Behaviors such as plagiarism, cheating during assessments, and unethical collaboration practices erode both the ethical development of students and the credibility of academic institutions. Effectively confronting these issues demands flexible evaluation models that accommodate behavioral uncertainty and contextual variability. Within this framework, the FAIM model, by integrating fuzzy logic and neutrosophic reasoning, provides a robust mechanism for assessing academic integrity, offering more nuanced and precise evaluations compared to conventional methods [4, 5].

Further elaborating on the methodological contribution of FAIM, the model addresses ethical ambiguity through a neutrosophic approach, which represents student behavior across three dimensions: truth (V), indeterminacy (I), and falsehood (F). This triadic framework enables the categorization of integrity levels using linguistic descriptors linked to numerical SVN values, thus reflecting the inherent complexity of moral decision-making in academic settings. By facilitating more informed and adaptive interventions, FAIM strengthens institutional efforts to cultivate a resilient culture of academic integrity [15].

2. Materials and Methods

The methodology of this study is based on the development and validation of the FAIM model through simulated scenarios reflecting academic dishonesty. It integrates fuzzy logic and neutrosophic reasoning to evaluate integrity levels under conditions of uncertainty. Key variables—motivation, justification, and opportunity—were operationalized to capture the complexity of student behavior.

2.1. Fundamentals of Fuzzy Logic Applied to Ethical Evaluation in Education

Fuzzy logic is a method of thinking that gets beyond the rigidity of the traditional binary approach by allowing a statement to have numerous degrees of truth. This capacity is particularly helpful in complicated situations when moral judgments are not always clear-cut but rather fall somewhere on a spectrum of doubt, like when evaluating academic honesty. A fuzzy set is described mathematically as a membership function that allocates a value in the interval [0,1] to each element $\boldsymbol{x}$ of a reference set $\boldsymbol{S}$ [6].

$$\boldsymbol{A}: \boldsymbol{S} \rightarrow [\mathbf{0}, \mathbf{1}] \ \boldsymbol{Where}\ \boldsymbol{\mu A}(\boldsymbol{x}) \in [\mathbf{0}, \mathbf{1}] \tag{1}$$

The element's level of membership in the set is indicated by this value. Strong membership is indicated by values around 1, whereas low membership (or considerable doubt) is indicated by values near 0. Fuzzy sets enable the portrayal of the ambiguity present in real-life circumstances, such as students' moral decisions in virtual settings, in contrast to traditional or Boolean sets, which only permit presence or absence ($\boldsymbol{\mu A}(\boldsymbol{x}) = \mathbf{1}\ \boldsymbol{or}\ \mathbf{0}$). This tool is essential to the FAIM model because it allows for the incremental quantification of actions that are difficult to categorize strictly dichotomously, like the reason or justification for dishonest acts.

2.2. Linguistic Variables and Membership Functions in the FAIM Model

Fuzzy logic is essential for handling the ambiguity and uncertainty that come with assessing academic integrity in the framework of the FAIM (Fuzzy-Neutrosophic Academic Integrity Model). The usage of linguistic variables, or natural language phrases represented by fuzzy sets defined across a particular discourse universe, is a crucial component of this methodology [7,8,9].

For academic decision-makers, linguistic characteristics like "low integrity," "moderate justification," or "high motivation for dishonesty" make the system's outputs easier to understand. The granularity of uncertainty must be determined before establishing these variables. The cardinality of the language label set used to describe uncertain information is referred to as this granularity; in other words, it is the degree to which we divide the spectrum of evaluation.

2.2.1. Cardinality of Linguistic Labels in FAIM

In FAIM, the main variables related to academic integrity—motivation, justification, and opportunities for dishonesty—are modeled with fuzzy-neutrosophic linguistic labels. Cardinality refers to the number of labels used to discretize or granulate the continuous scale of each variable.

a. Election of the label number.

Generally, use between 5 and 7 labels to capture a balance between precision and simplicity of interpretation. In the case of FAIM, the typical granularity is 5 linguistic labels:

- Very Low (VL)
- Low (L)
- Medium (M)
- High (H)
- Very High (VH)

These labels allow us to assign values of belonging not only to the degree of truth (T) but also to indeterminacy (I) and falsity (F) in the neutrosophic framework.

b. Justification of this cardinality

- With fewer than 5 labels (for example, 3: low, medium, high), the model loses its ability to differentiate subtle patterns of behavior.
- With more than 7, interpretation by researchers and academic administrators becomes impractical.
- 5 labels are considered an optimal level of granularity for representing uncertain information operationally and understandably.

c. Relationship with uncertainty and granularity

Each label represents a fuzzy-neutrosophic set with three membership values

- $T(x)$: degree of truth (e.g., the actual level of motivation toward cheating).
- $I(x)$: degree of indeterminacy (e.g., when the student displays ambiguous behavior).
- $F(x)$: degree of falsity (e.g., denial that such motivation is present)

Granularity comes from how finely the scale of each variable is divided. By using five labels, FAIM manages to capture variations in integrity levels with sufficient resolution to differentiate simulated and real-life scenarios.

d. Practical implications

In neutrosophic contexts, the intermediate value $I(x)$ becomes crucial for describing cases of ambiguity where students are neither clearly honest nor dishonest.

2.2.2. Degree of membership

The degree of membership of a given element $\boldsymbol{x}$ to a fuzzy set $\boldsymbol{M}(\boldsymbol{x})$ is determined using **membership functions**. In the FAIM system, two commonly used membership functions are the **triangular** and **trapezoidal** functions, which are described as follows [11].

Universe of discourse

a. Triangular Membership Function

$$x \in [0,1] \tag{2}$$

The **triangular function** is defined by three parameters: the lower limit $\boldsymbol{a}$, the upper limit $\boldsymbol{b}$, and the modal (peak) value $\boldsymbol{m}$, where $\boldsymbol{a} < \boldsymbol{m} < \boldsymbol{b}$. It is useful for modeling concepts with a single clear peak of membership [10,11].

$$\mu(x) = \begin{cases} 0 & si\ x \leq a \\ \dfrac{x-a}{m-a} & si\ a < x \leq m \\ \dfrac{b-x}{b-m} & si\ m < x \leq b \\ 0 & si\ x \geq b \end{cases} \tag{3}$$

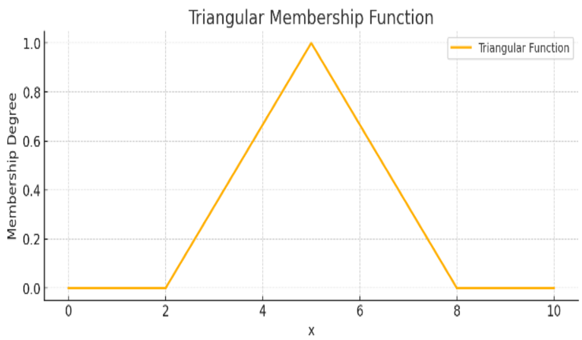


Fig. 1. A Triangular Membership Function

Medium (triangular) (a, b, c) = (0.25,0.50,0.75).

$$\mu_M(x) = \begin{cases} \dfrac{x-0.25}{0.50-0.25}, & 0.25 < x \leq 0.50 \\ \dfrac{0.75-x}{0.75-0.50}, & 0.50 < x < 0.75 \\ 0, & \text{otherwise} \end{cases}$$

b. Trapezoidal Membership Function

The trapezoidal function is defined by four parameters: the lower limit a, the upper limit d, and the start and end of the plateau b and c, respectively. It models situations where a concept holds strongly over a range of values [12,13].

$$\mu(x) = \begin{cases} 0 & si\ x \le a \\ \dfrac{x-a}{b-a} & si\ a < x \le b \\ 1 & si\ b < x \le c \\ \dfrac{d-x}{b-c} & si\ c < x \le d \\ 0 & si\ x > d \end{cases} \quad (4)$$

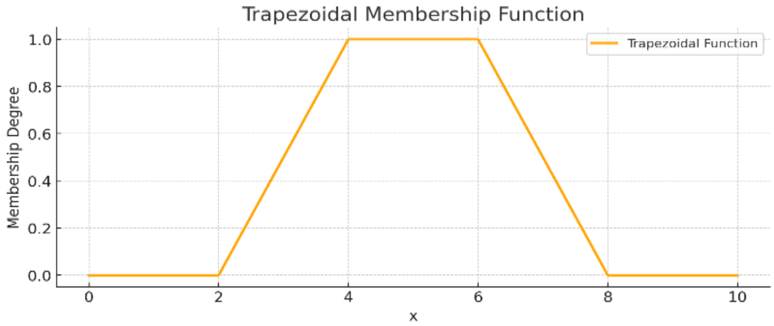


Fig. 2. Trapezoidal Membership Function

Membership functions

Low (trapezoidal, left shoulder) (a, b, c, d) = (0,0,0.2,0.4)

$$\mu_L(x) = \begin{cases} 1, & 0 \le x \le 0.2 \\ \dfrac{0.4-x}{0.4-0.2}, & 0.2 < x < 0.4 \\ 0, & x \ge 0.4 \end{cases}$$

High (trapezoidal, right shoulder) (a, b, c, d) = (0.60,0.80,1,1)

$$\mu_H(x) = \begin{cases} 0, & x \le 0.60 \\ \dfrac{x-0.60}{0.80-0.60}, & 0.60 < x < 0.80 \\ 1, & 0.80 \le x \le 1 \end{cases}$$

These membership functions are applied within FAIM to model key variables such as motivation, justification, and opportunity for dishonest behavior. By assigning degrees of truth to these subjective factors, FAIM enables a nuanced and flexible evaluation of student integrity under uncertain conditions.

3. Results

A fuzzy logic model was used to describe the uncertainty involved in ethical behavior to evaluate university students' levels of academic integrity. The method converts linguistic results into a representative numerical value by fuzzy inference and defuzzification utilizing the Centroid or Center of Gravity (GOC). The GOC method's primary benefit is that it just requires the membership functions of the linguistic labels associated with each variable to be defined, eliminating the requirement for human coefficient adjustment [14].

The formula applied is:

$$\mathrm{GOC} = \frac{\int x\cdot\mu(x)dx}{\int \mu(x)dx} \tag{5}$$

where $\mu(x)$ is a measure of how much each value belongs to the discourse universe. The precision of the outcome increases with the fineness of the integration step. Three input variables linked to academic dishonesty—motivation, justification, and opportunity—were used to develop this system during the COVID-19 pandemic. Academic integrity was the output variable, and it was denoted by the linguistic phrases low, medium, and high.

The membership functions used were

- Low: trapezoidal function with points (0,0,0.2,0.5).
- Medium: triangular function with points (0.2,0.5,0.8).
- High: trapezoidal function with points (0.5,0.8,1,1).

With these functions (breakpoints ≈ 0.2, 0.25, 0.5, 0.75, 0.8, and clipping levels 0.4/0.6/0.4), the aggregated black curve and a centroid close to 0.45 are obtained..

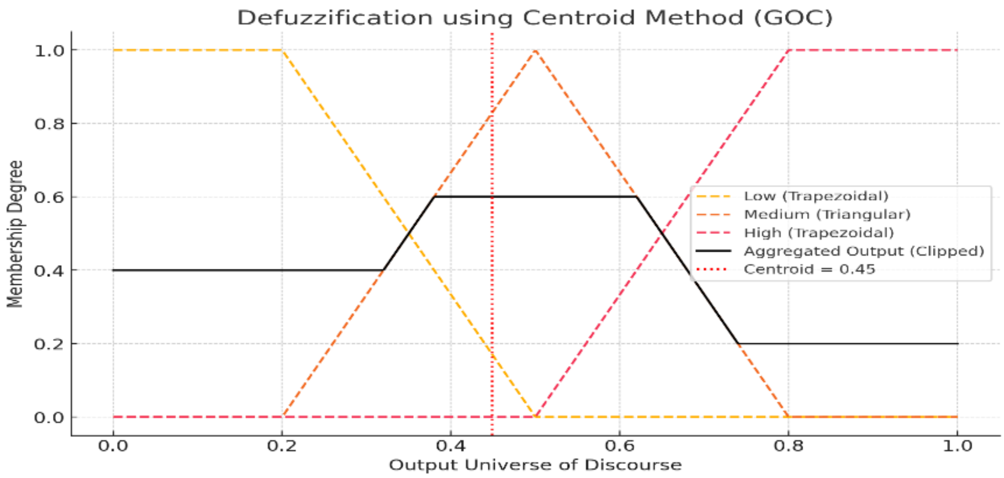
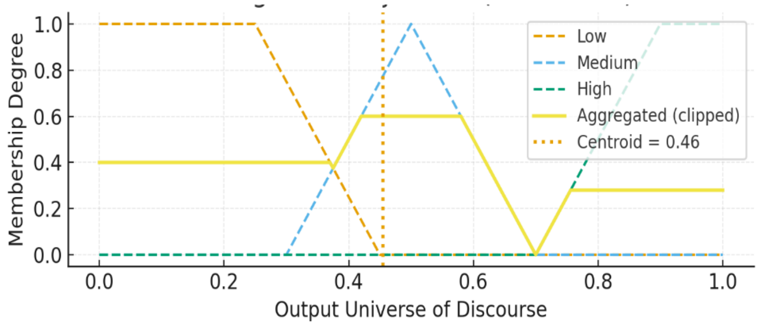


Fig. 3. Defuzzification using Centroid Method (GOC)

The graph illustrates the centroid method (GOC) defuzzification procedure used to evaluate academic integrity in a particular FAIM model scenario. An aggregated output function was created by combining the levels of belonging ascribed to the linguistic labels (Low = 0.4, Medium = 0.6, and High = 0.2) into a single trimmed curve. The computed centroid, which is situated at a location that indicates a degree of integrity marginally over average, is the numerical number that summarizes the fuzzy assessment. This finding suggests that while low and ambiguity are factors that diminish integrity, moderate ethical behavior is more common. The methodology shows how subjective and ambiguous views may be converted into quantitative findings that can be applied to academic decision-making.

Tight configuration (z* ≈ 0.455)



a. Fuzzy output and "clipping"

Universe: x ∈ [0,1]

Sets and cut levels (firing strengths):

Low trapezoidal (0,0,0.25,0.45), αL=0.40

$$\mu_L(x) = \begin{cases} 1, & 0 \leq x \leq 0.25 \\ \dfrac{0.45 - x}{0.20}, & 0.25 < x < 0.45 \\ 0, & \text{otro} \end{cases}$$

$$\tilde{\mu}_L(x) = \min\{\mu_L(x), 0.40\}$$

Medium triangular (0.30,0.50,0.70), αM=0.60.

$$\mu_M(x) = \begin{cases} \dfrac{x - 0.30}{0.20}, & 0.30 < x \leq 0.50 \\ \dfrac{0.70 - x}{0.20}, & 0.50 < x < 0.70 \\ 0, & \text{otro} \end{cases}$$

$$\tilde{\mu}_M(x) = \min\{\mu_M(x), 0.60\}$$

High trapezoidal (0.70,0.90,1,1), αH=0.26.

- **High** trapezoidal $(0.70, 0.90, 1, 1)$, $\alpha_H = 0.26$

$$\mu_H(x) = \begin{cases} \dfrac{x - 0.70}{0.20}, & 0.70 < x < 0.90 \\ 1, & 0.90 \leq x \leq 1 \\ 0, & \text{otro} \end{cases}$$

$$\tilde{\mu}_H(x) = \min\{\mu_H(x), 0.26\}$$

Aggregation (maximum):

$$\mu_{\text{agg}}(x) = \max\{\tilde{\mu}_L(x), \tilde{\mu}_M(x), \tilde{\mu}_H(x)\}. \quad (6)$$

b. Breakpoints (where slopes change)

- **Low** falls below 0.40 at x=0.37.
- **Medium** reaches 0.60 at x=0.42, decreases below 0.60 at x=0.58
- **High** reaches 0.26 at x=0.752.
- Low–Medium intersection at x=0.375.

c. Aggregated function μagg(x) by intervals

$$\mu_{\text{agg}}(x)=\begin{cases}0.40, & 0\le x\le 0.37\\ \dfrac{0.45-x}{0.20}, & 0.37<x\le 0.375\\ \dfrac{x-0.30}{0.20}, & 0.375<x\le 0.42\\ 0.60, & 0.42<x\le 0.58\\ \dfrac{0.70-x}{0.20}, & 0.58<x\le 0.70\\ \dfrac{x-0.70}{0.20}, & 0.70<x\le 0.752\\ 0.26, & 0.752<x\le 1.\end{cases}$$

d. Defuzzification by centroid

$$z^{\backslash *}=\frac{\int_0^1 x\,\mu_{\text{agg}}(x)\,dx}{\int_0^1 \mu_{\text{agg}}(x)\,dx}=\frac{N}{D}. \tag{7}$$

e. Calculations by segments

1. $x\in[0,0.37], \mu=0.40$
   $A_1=0.148, M_1=0.02738$
2. $x\in(0.37,0.375], \mu=2.25-5x$
   $A_2=0.00194, M_2=0.00072$
3. $x\in[0.375,0.42], \mu=5x-1.5$
   $A_3=0.02194, M_3=0.00876$
4. $x\in[0.42,0.58], \mu=0.60$
   $A_4=0.096, M_4=0.048$
5. $x\in[0.58,0.70], \mu=3.5-5x$
   $A_5=0.036, M_5=0.02232$
6. $x\in[0.70,0.752], \mu=5x-3.5$
   $A_6=0.00676, M_6=0.00497$
7. $x\in[0.752,1], \mu=0.26$
   $A_7=0.06448, M_7=0.05648$

f. Totals

$$D=\sum A_i=0.375115,\quad N=\sum M_i=0.168631.$$

$$z^{\backslash *}=\frac{N}{D}=\frac{0.168631}{0.375115}=0.44954\approx 0.45.$$

3.1. Input data

The input data for individual aggregation by scenario consists of SVN values—Truth (V), Indeterminacy (I), and Falsity (F)—assigned to each case. These values reflect the ethical behavior of students under different academic conditions. By analyzing each scenario independently, we obtain a precise profile of integrity levels through neutrosophic reasoning.

Table 1. Neutrosophic Results by Scenario

Scenario	SVN	Closest Linguistic Term	Distance
Scenario 1	(0.12, 0.91, 0.88)	Very Very Bad (MMM)	0.03
Scenario 2	(0.32, 0.68, 0.68)	Bad (MA)	0.0755
Scenario 3	(0.18, 0.85, 0.82)	Very Bad (MM)	0.0283

By comparing the SVN values (Truth, Indeterminacy, Falsehood) with a previously established scale of linguistic terms, the neutrosophic analysis's findings enable each scenario to be categorized based on its degree of perceived academic integrity. With ratings of 0.12, 0.91, and 0.88, Scenario 1 was categorized as "Very Poor (VVP)," suggesting a critical degree of integrity, marked by limited truth and high indeterminacy and falsehood. With ratings of 0.32, 0.68, and 0.68, Scenario 2 was categorized as "Poor (PO)," indicating inadequate ethical behavior, however, not as bad as Scenario 1. Finally, Scenario 3, which had values of 0.18, 0.85, and 0.82, was categorized as "Very Poor (VPO)," suggesting a setting with significant ethical flaws but marginally better than the previous scenario.

By using Euclidean distances to measure proximity to language concepts, this classification makes it possible to interpret integrity levels flexibly and gradually, giving educational institutions a helpful tool for setting priorities for training interventions.

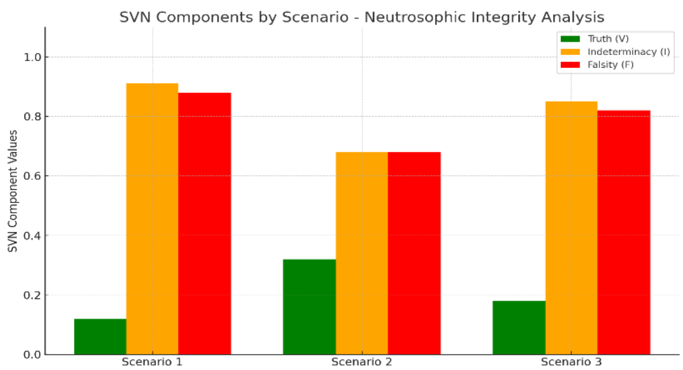


Fig. 4. SVN Components by Scenario - Neutrosophic Integrity Analysis

- Green (Truth): Reflects the degree of ethical behavior observed.
- Orange (Indeterminacy): Indicates the level of ambiguity or ethical uncertainty in the scenario.
- Red (Disingenuousness): Measures the inclination toward academically dishonest behavior

The most critical profile in terms of academic integrity is shown by Scenario 1, according to the SVN component graph (Truth, Indeterminacy, Falsehood). Its highly high indeterminacy (0.91) and falsity (0.88) values, as well as its extremely low truth (0.12) score, demonstrate a strong tendency toward dishonesty and a lack of ethical clarity. Scenario 2, on the other hand, exhibits a significant improvement: falsehood (0.68) and indeterminacy (0.68) are decreased, and its level of truth (0.32) is the greatest of the three scenarios, making it the most advantageous setting from an ethical perspective.

3.2. Comparative Interpretation of Fuzzy vs. Neutrosophic Models in Academic Integrity Assessment.

Important distinctions in the ways each model assesses academic integrity are shown by the comparative study. Scenario 2 significantly outperforms the others (score: 0.96), whereas Scenario 1 ranks lowest (0.33), showing serious ethical difficulties. The fuzzy model provides accurate numerical results. Conversely, the neutrosophic model provides nuanced interpretations based on truth, indeterminacy, and falsehood and is represented inversely by closeness scores (1 − distance). Interestingly, Scenario 3's precision score is marginally higher than Scenario 1's, indicating that the neutrosophic model picks up on minute contextual variations that fuzzy inference alone is unable to pick up. Consistency is shown by the two models' alignment in giving Scenario 2 the highest ranking, but the hybrid use of both improves comprehension overall. This comparison demonstrates how combining the two approaches improves ethical diagnostics in learning environments [16].

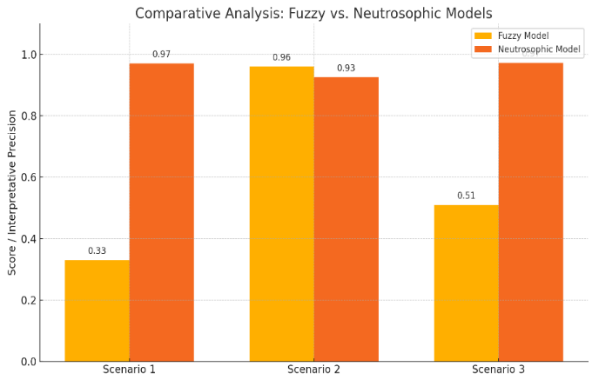


Fig. 5. Comparative Analysis: Fuzzy vs. Neutrosophic Models

- **Fuzzy Model (Yellow):** Represents the quantitative score obtained after defuzzification (centroid method)
- **Neutrosophic Model (Orange):** It shows an interpretive score based on the inverse proximity to the linguistic terms (the shorter the distance, the greater the precision**)**

3.3. Fuzzy-Neutrosophic Hybrid Model (FAIM).

The FAIM hybrid model combines the interpretive depth of Neutrosophy with the quantitative precision of fuzzy logic for assessing academic integrity. In the fuzzy phase, factors like motivation and opportunity are converted into scores using centroid inference. The neutrosophic phase adds complexity by modeling ambiguity and untruth with SVN values. Integration of both methods results in a flexible and reliable ethical ranking system. FAIM supports comparison across students or contexts and guides preventive educational strategies. It achieves a balance between semantic insight and numerical rigor, ideal for uncertain academic environments [17, 18].

3.3.1. Radar Chart – Comparison of Fuzzy, Neutrosophic, and Hybrid Models.

The radar chart is a graphical tool for visualizing multivariate data in a circular format. It enables comparison of different models or scenarios across common dimensions. In academic integrity analysis, it highlights each model's strengths and weaknesses.

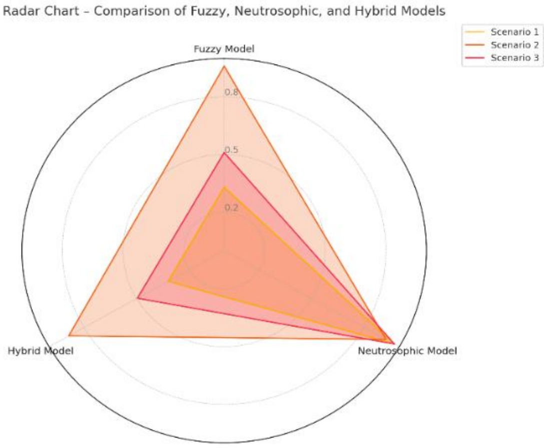


Fig. 6. Radar Chart – Comparison of Fuzzy, Neutrosophic, and Hybrid Models

The radar chart allows simultaneous comparison of fuzzy, neutrosophic, and hybrid models across academic integrity scenarios. Each line represents a scenario, highlighting similarities or differences in model evaluations. Scenario 2 consistently scores highest, reflecting a stronger ethical profile. The hybrid model smooths differences, offering a balance between numerical precision and interpretive depth. This makes it a more reliable tool for ethical assessment. Overall, the chart reinforces the FAIM model's value in analyzing complex behaviors under uncertainty.

4. Discussion.

In their study [1], Rettinger and Kramer looked at the personal and contextual elements that lead to academic dishonesty among college students. One of their primary accomplishments is the justification of dishonest behavior and contextual chances as crucial elements. These elements are consistent with opportunity, justification, and motivation—the three elements considered in FAIM. The study finds that in flexible educational situations, like virtual learning, it is more challenging to detect etiological behavior. This emphasizes the necessity for models like FAIM that include mechanisms to manage ambiguity and uncertainty.

Lancaster and Cotarlan [2] looked at how the pandemic caused a sudden change to distance learning, which increased the usage of impersonation services and plagiarism. They note in their study that the new digital conditions overpowered the old control systems. By emphasizing the need for models that reflect the complexity of novel learning contexts and enable integrity evaluation using uncertainty-sensitive methodologies, this work aligns with the FAIM approach.

To assess the ethical values of engineering students, Kumar and Singh [3] developed a methodology based on fuzzy logic. This approach made it possible to manage subjective perceptions and imprecise data, providing a more contextualized view of ethical behavior. Despite not taking into account 0neutrosofía, their model offers a solid foundation that supports the use of computational tools to measure complex ethical dimensions. This concept enhances FAIM by demonstrating how fuzzy logic improves evaluation in situations where moral standards are vague and unclear.

5. Conclusions.

Fuzzy logic and neutrosophic theory are combined in the hybrid model FAIM, which provides a thorough and flexible method of evaluating university students' academic integrity. The model captures the degree of ethical behavior as well as the ambiguity and uncertainty surrounding it by fusing the contextual depth of neutrosophic reasoning with the quantitative accuracy of fuzzy inference. The neutrosophic phase enhances the analysis with truth, indeterminacy, and falsity dimensions, while the fuzzy phase offers unambiguous number ratings based on factors including opportunity, motive, and justification. These outputs provide a more accurate way to categorize and rank integrity levels across scenarios when combined. The hybrid model's discriminative capacity is further validated using visual aids like radar maps and ROC curves. The hybrid approach performs better than individual models in terms of interpretability and diagnostic strength, according to comparative studies. For educational institutions looking to encourage moral behavior, FAIM is a useful tool for making decisions. Because of its adaptability, it may be used in both in-person and online learning environments. In the end, FAIM improves the caliber and equity of academic assessments under challenging and unpredictable circumstances.

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