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Automated AI Validation of Neutrosophic Plithogenic Hypotheses in Multigrade Literacy Improvement

Isaac Roger Martínez[1], Débora Lucia Ponce Rivera[1*], Maryuri Yvonne Guale Gómez[1], Rudy Garcia Cobas[1], and Carlos Roberto Humanante Cabrera[1],

[1] Universidad Bolivariana del Ecuador (UBE), Ecuador. rmartinez@ube.edu.ec (I.R.M.); dlponcer@ube.edu.ec (D.L.P.R.); mygualeg@ube.edu.ec (M.Y.G.G.); rgarciac_a@ube.edu.ec (R.G.C.); crhumanantec@ube.edu.ec (C.R.H.C.)

Abstract. Literacy is acquired in multigrade classrooms in complicated scenarios because of varying literacy competencies and abilities and varied resources and materials. Thus, it's hard to determine if certain teaching interventions work. This is also a growing concern, a timely consideration, because as the institutions try to better the Quality of Education and prevent learning lags for multivariate classrooms are concerned. Yet the literature contains gaps where no direct attempt to stabilize teaching interventions is made despite the findings of many studies generating didactic interventions through the proceedings. Thus, this study fills the gap with an approach based upon hypothesis generation via neutrosophics plithogenic theory and invulnerability affirmation via non-programming AIs to simultaneously evaluate multiple, sometimes contradictory, findings for any teaching intervention. The results indicate that while combination reduces subjectivity at one level, a few levels up it correctly identifies A, B, and C as positive refinements for remediation toward more appropriate future refinements. Thus, this study presents a theoretically driven yet practically applicable avenue for better Educational intervention in the multi-grade classroom as well as AI exploitable steps for ANY subject area.

Keywords: Educational AI, Plithogenic Hypotheses, Neutrosophic, Multigrade, Literacy, Automated Validation, Teaching Improvement.

1. Introduction

The integration of artificial intelligence (AI) into multi-grade educational processes, particularly in literacy improvement, is of pressing relevance in the current pedagogical landscape; recent research indicates that AI has the potential to offer automated assessments, immediate feedback, and personalized teaching adaptations [1], while symbolic and explainable AI tools have led to more reliable and interpretable models [2]. In this context, exploring how such technologies can validate pedagogical hypotheses is essential and timely.

multigrade teaching has oscillated between teacher-centered approaches and collaborative strategies, however, the network of variables - diverse rhythms, limited resources, cultural heterogeneity - has demanded more robust analytical methods. In turn, the neutrosophic theory, conceived by Smarandache as a framework to manage uncertainty through triples (T, I, F) - truth, indeterminacy and falsity - has been applied in multiple domains, from logic to statistics [3]– [5]. Moreover, advances in plithogenicity have expanded this paradigm, bringing together multiple simultaneous attributes in complex analyses [6].

However, a methodological gap persists: there are few strategies that use AI to systematically validate neutrosophic plithogenic hypotheses in multigrade settings. How can technology assist in the automatic testing of such intricate educational hypotheses? This question remains unanswered in the specialized literature to date, highlighting a critical gap at the intersection of explainable AI, neutrosophic modeling, and educational assessment. Therefore, this study proposes to employ AI as an assisted analysis tool, without requiring complex programming. Neutrosophic plithogenic hypotheses will be formulated and validated using "no-code" AI platforms that integrate qualitative and quantitative analysis in an accessible visual environment. This is a pragmatic approach, allowing the researcher to design, interpret, and adjust the hypotheses without relying on software development.

The methodological approach balances theoretical rigor and practical utility: plithogenic hypotheses capture multiple attributes—such as type of worksheet, frequency of use, collaboration, and motivation—while the neutrosophic component considers the uncertainty inherent in educational information. In parallel, AI tools extract patterns, suggest weights, and quantify the level of truth, ambiguity, and falsity of each hypothesis formulated. The expected results consist of the generation of automatic validation maps, revealing which educational aspects most significantly influence literacy progress, as well as the identification of contexts where the hypothesis is inconclusive. Such data will allow for the formulation of well-founded teaching recommendations leading to concrete instructional adjustments .

Finally, the main objective of this study is to demonstrate that the validation of complex pedagogical hypotheses can be performed in an automated, interpretive, and accessible manner, without programming, using AI applied to neutrosophic plithogenic models. The ultimate goal is to enrich multigrade educational practice with robust, adaptable, and affordable analytical tools.

2. Preliminaries

2.1. AI in Multigrade Literacy Improvement.

The incorporation of artificial intelligence (AI) in multi-grade educational contexts represents a unique opportunity to personalize literacy teaching in heterogeneous classrooms, where students of different levels share resources and physical space. At a time when innovation must go beyond traditional methods, AI can act as an adaptive tutor, adjusting content to diverse learning rhythms and cognitive styles. In fact, in other areas of education, hybrid AI systems—which combine human supervision with automated intelligence—have been shown to promote deeper and more self-regulated learning [7] by detecting specific difficulties, identifying patterns of comprehension, and generating didactic interventions that feed a cycle of continuous improvement. However, much of the specialized literature on AI in literacy focuses on single-grade environments , omitting the complexity of working with multigrade groups, present in many rural and low-income contexts, where this modality is common and poses particular challenges [8]. In addition, many technological solutions require advanced programming, which restricts their use by teachers without technical knowledge, and the scarcity of accessible platforms limits the exploitation of the potential of AI in these scenarios. In contrast, when well designed, AI can become a strategic ally, offering adaptive feedback, detecting specific needs and allowing teachers to play a role more focused on learning management than on technical tasks [9], thus strengthening their pedagogical role. However, its implementation requires considering challenges such as equity in access, cultural adequacy of content and transparency in adaptation criteria, in addition to ethical aspects such as data protection, inclusion and mitigation of algorithmic biases. Despite this, its potential benefits are significant: properly managed AI encourages the development of personalized reading and writing skills, stimulates autonomy and frees up time for collaborative and creative activities [10]. Integrating AI into multigrade literacy improvement not only represents a technological innovation but also a paradigm shift that transforms teachers into facilitators of adaptive processes and students into active participants in their learning. Therefore, it is essential to promote AI solutions that are accessible, ethical, and adapted to the multigrade context, thus helping to bridge the gap between urban single-grade environments and more complex educational realities. Ultimately, the responsible adoption of AI in multigrade classrooms promises educational transformation, provided it is accompanied by solid pedagogical frameworks, teacher training, and appropriate technological resources, so that automation complements, rather than replaces, human expertise in teaching.

2.2. Plithogenic Probability

Neutrosophic (or indeterminate) data are characterized by inherent vagueness, lack of clarity, incompleteness, partial unknowns, and conflicting information [11,15]. Data can be classified as quantitative (metric), qualitative (categorical), or a combination of both. Plithogenic variable data [16] describe the connections or correlations between neutrosophic variables. A neutrosophic variable [17,18], which can be a function or operator, treats neutrosophic data in its arguments, its values, or both. Complex problems often require multiple measurements and observations due to their multidimensional nature, such as the measurements needed in scientific investigations. Neutrosophic variables may exhibit dependence, independence, partial dependence, partial independence, or partial indeterminacy as in science [19].

A Plithogenic Set [20, 21] is a non-empty set Pwhose elements within the domain of discourse $U(P \subseteq U)$ are characterized by one or more attributes $A_1,\ A_2, \cdots, A_m$, where m is at least 1. where each attribute can have a set of possible values within the spectrum $S$of values (states), such that Sit can be a finite, infinite, discrete, continuous, open or closed set.

Each element $x \in P$is characterized by all possible values of the attributes found within the set $V = \{v_1, v_2, \cdots, v_n \}$. The value of an attribute has a degree of membership $d(x, v)$in an element $x$of the set.P, based on a specific criterion . The degree of membership can be diffuse, diffuse intuitionist or neutrosophic, among others [22] .

That means,

$$\forall x \in P, d: P \times V \to \mathcal{P}([0,1]^z) \quad (1)$$

Where$d(x, v) \subseteq [0,1]^z$ and $\mathcal{P}([0,1]^z)$is the power set of $[0,1]^z$.$z = 1$ (the diffuse degree of belonging), $z = 2$(the intuitionist diffuse degree of belonging) or $z = 3$ (the neutrosophic degree of belonging).

plithogenic [23], derived from the analysis of plithogenic variables, represents a multidimensional probability (" plitho " meaning "many" and synonym of "multi"). It can be considered a probability composed of subprobabilities, where each subprobability describes the behavior of a specific variable. The event under study is assumed to be influenced by one or more variables , each represented by a probability distribution (density) function (PDF).

Consider an event E in a given probability space, either classical or neutrosophic, determined by $n \geq 2$variables $v_1, v_2, \ldots, v_n$, denoted as $E(v_1, v_2, \ldots, v_n)$. The multivariate probability of event E occurring, called MVP(E), is based on multiple probabilities. Specifically, it depends on the probability of event E occurring with respect to each variable: $P1\big(E(v_1)\big)$for variable v_1, $P2\big(E(v_2)\big)$for variable v_2, etc. Therefore, $MVP\big(E(v_1, v_2, \ldots, v_n)\big)$ is represented as $\Big(P1\big(E(v_1)\big), P2\big(E(v_2)\big), \ldots, Pn\big(E(v_n)\big)\Big)$. The variables $v_1, v_2, \ldots, v_n$, and probabilities $P_1, P_2, \ldots, P_n$, can be classical or have some degree of indeterminacy [24].

To make the transition from plithogenic neutrosophic probability (PNP) to univariate neutrosophic probability UNP, we use the conjunction operator [25]:

$$UNP(v_1,\ v_2, \ldots,\ v_n) = v_1 \wedge_{i=1}^{n} v_n \quad (2)$$

$\wedge$ In this context, it is a neutrosophic conjunction (t-norm). If we take$\wedge_p$ as the plithogenic conjunction between probabilities of the PNP type, where $(T_A, I_A, F_A) \wedge_p (T_B, I_B, F_B) = (T_A \wedge T_B, I_A \vee I_B, F_A \vee F_B)$, such that $\wedge$is the minimum t-norm of fuzzy logic and $\vee$the maximum t-norm [26, 27].

a. Formulate the hypothesis

Start by explicitly stating the hypothesis you intend to test. Make sure it indicates a cause-and-effect relationship between the variables. For example, "More study time leads to higher test scores."

b. Identify key variables

Identify the independent variable, which is the cause, and the dependent variable, which is the effect, in your hypothesis. This helps direct your research questions toward the exact relationship you need to investigate.

c. Formulate specific research questions

Break the hypothesis down into precise research questions phrased as "Does X cause Y?" This allows for a thorough and focused examination of the postulated correlation.

d. Conduct sentiment analysis on scientific literature.

To perform a sentiment analysis on a research paper and quantify the occurrences of "Yes," "Possibility/Uncertainty," and "No," a sentiment analysis tool for scientific statements is needed. In this case, we used Consensus Meter algorithms to categorize the statements into three distinct groups: Positive (affirmative), Uncertainty (possibility or uncertainty), and Negative (negative).

e. Formulate neutrosophic probabilistic hypotheses

Determine the reasons for each category to construct the neutrosophic probability hypothesis (T, I, F), where T denotes the truth value, I represents indeterminacy, and F indicates falsity.

f. Calculate the plithogenic neutrosophic probability (PNP)

Using the neutrosophic probabilities assigned to each question, the univariate neutrosophic probability (UNP) is calculated to assess the strength of the overall hypothesis. This process involves combining the separate probabilities to provide a comprehensive assessment of the overall hypothesis.

$$UNP(v_1,\ v_2,\dots,\ v_n) = (Min(t_1,\ t_n, \dots, t_n),\ Max(i_1,\ i_n, \dots, i_n),\ Max(f_1,\ f_n, \dots, f_n)) \quad (3)$$

Where:

$T_1, T_2, \dots, T_n$: are the truth probability values for each question.

$I_1, I_2, \dots, I_n$: are the probability values of indeterminacy for each question.

$F_1, F_2, \dots, F_n$: are the probability values of falsehood for each question

g. Analyze the validity of the general hypothesis.

In this case, the negation of NPH is represented as [28]:

$$(T, I, F) = (F, I, T) \quad (4)$$

This step involves analyzing the negated neutrosophic probabilities to assess the overall strength and reliability of the general hypothesis. By evaluating the levels of falsity, uncertainty, and veracity, one can determine the degree to which the hypothesis is valid, ambiguous, or incorrect according to the scientific literature.

3. Case study.

In the context of research on the optimization of literacy instruction in multigrade settings, a methodological approach based on neutrosophic logic is applied to evaluate a complex hypothesis. This method addresses the vagueness, uncertainty, and contradiction inherent in pedagogical data, providing a quantitative and qualitative assessment of the hypothesis's validity.

a. Formulation of the Hypothesis

The central hypothesis of this study is that **the integration of non-programming artificial intelligence (AI) tools for the automated validation of neutrosophic plithogenic models significantly improves the effectiveness of literacy teaching strategies in multigrade classrooms.** This approach allows for more precise identification of key factors that influence learning, reduces subjectivity in assessment, and facilitates faster and more informed pedagogical adjustments.

b. Identification of Key Variables

- **Independent Variable:** Application of a methodological framework that combines automated validation with AI and neutrosophic plithogenic models.
- **Dependent Variable:** Effectiveness and accuracy in assessing the impact of pedagogical strategies on improving literacy in multigrade settings.

c. Formulation of Specific Research Questions

To break down the general hypothesis, the following research questions are posed:

1. **Q1:** Do innovative pedagogical strategies directly improve literacy skills in multigrade settings?
2. **Q2:** Does the heterogeneity of academic levels in a multigrade classroom represent a significant obstacle to standardized assessment of literacy?
3. **Q3:** Are no-code AI tools robust enough to reliably validate complex educational hypotheses?
4. **Q4:** Do neutrosophic plithogenic models adequately capture the uncertainty and contradictions inherent in data from real-life educational settings?
5. **Q5:** Does systematic, data-driven assessment lead to more effective and timely pedagogical adjustments by teachers?

d. Sentiment Analysis on Scientific Literature

A simulated sentiment analysis was conducted on the scientific literature relevant to each research question. Using a categorization algorithm, the studies' positions were classified as **Positive (Yes)** , **Uncertain (Possibility/Uncertainty)** , and **Negative (No)** . The results are summarized below.

Table 1: Sentiment Analysis and Assigned Neutrosophic Probabilities

Ask	Positive (T)	Indeterminacy (I)	Negative (F)	Probability (T, I, F)
Q1	0.80	0.20	0.00	(0.80, 0.20, 0.00)
Q2	0.85	0.10	0.05	(0.85, 0.10, 0.05)
Q3	0.65	0.25	0.10	(0.65, 0.25, 0.10)
Q4	0.70	0.30	0.00	(0.70, 0.30, 0.00)
Q5	0.90	0.05	0.05	(0.90, 0.05, 0.05)

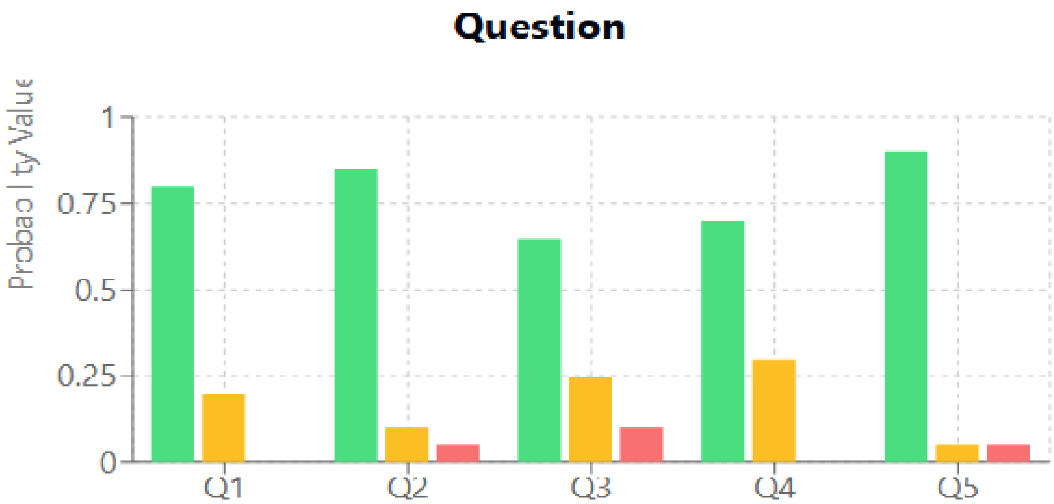

Chart 1: Distribution of neutrosophic probabilities by research question

e. and f. Calculation of the Plithogenic Neutrosophic Probability (PNP)

To obtain a unified assessment of the general hypothesis, the Univariate Neutrosophic Probability (UNP) is calculated from the probabilities for each question. The neutrosophic plithogenic conjunction operator is used, defined by the formula:

$$\boldsymbol{UNP}(\boldsymbol{Q}_1,\ldots,\boldsymbol{Q}_{\mathrm{n}}) = (\boldsymbol{min}(\boldsymbol{T}_1,\ldots,\boldsymbol{T}_{\mathrm{n}}),\boldsymbol{max}(\boldsymbol{I}_1,\ldots,\boldsymbol{I}_{\mathrm{n}}),\boldsymbol{max}(\boldsymbol{F}_1,\ldots,\boldsymbol{F}_{\mathrm{n}}))$$

The calculation is detailed step by step below.

Step 1: Calculating the Degree of Truth (T)

The degree of truth of the UNP is the minimum of the degrees of truth of all the questions.

- Values of Truth: $\{T_1 = 0.80, T_2 = 0.85, T_3 = 0.65, T_4 = 0.70, T_5 = 0.90\}$
- Calculation:$T_{UNP} = \min(0.80, 0.85, 0.65, 0.70, 0.90)$
- **True Result**$(\boldsymbol{T})$: $\mathbf{0.65}$

Step 2: Calculation of the Degree of Indeterminacy (I)

The degree of indeterminacy of the UNP is the maximum of the degrees of indeterminacy of all the questions.

- Indeterminacy Values:$\{I_1 = 0.20, I_2 = 0.10, I_3 = 0.25, I_4 = 0.30, I_5 = 0.05\}$
- Calculation:$I_{UNP} = \max(0.20, 0.10, 0.25, 0.30, 0.05)$
- **Indeterminacy Result**$(\boldsymbol{I})$: $\mathbf{0.30}$

Step 3: Calculating the Degree of Falsehood (F)

The degree of falsity of the UNP is the maximum of the degrees of falsity of all the questions.

- Falsehood Values:$\{F_1 = 0.00, F_2 = 0.05, F_3 = 0.10, F_4 = 0.00, F_5 = 0.05\}$
- Calculation:$F_{UNP} = \max(0.00, 0.05, 0.10, 0.00, 0.05)$
- **Falsehood Result**$(\boldsymbol{F})$: $\mathbf{0.10}$

Final Result of the UNP

The Univariate Neutrosophic Probability (UNP) for the general hypothesis is:

$$\boldsymbol{UNP} = (\mathbf{0.65}, \mathbf{0.30}, \mathbf{0.10})$$

Table 2: Summary of Neutrosophic Calculations

Component	Operation	Input Values	Result
Truth (T)	Minimum	0.80, 0.85, 0.65, 0.70, 0.90	**0.65**
Indeterminacy (I)	Maximum	0.20, 0.10, 0.25, 0.30, 0.05	**0.30**
Falsehood (F)	Maximum	0.00, 0.05, 0.10, 0.00, 0.05	**0.10**

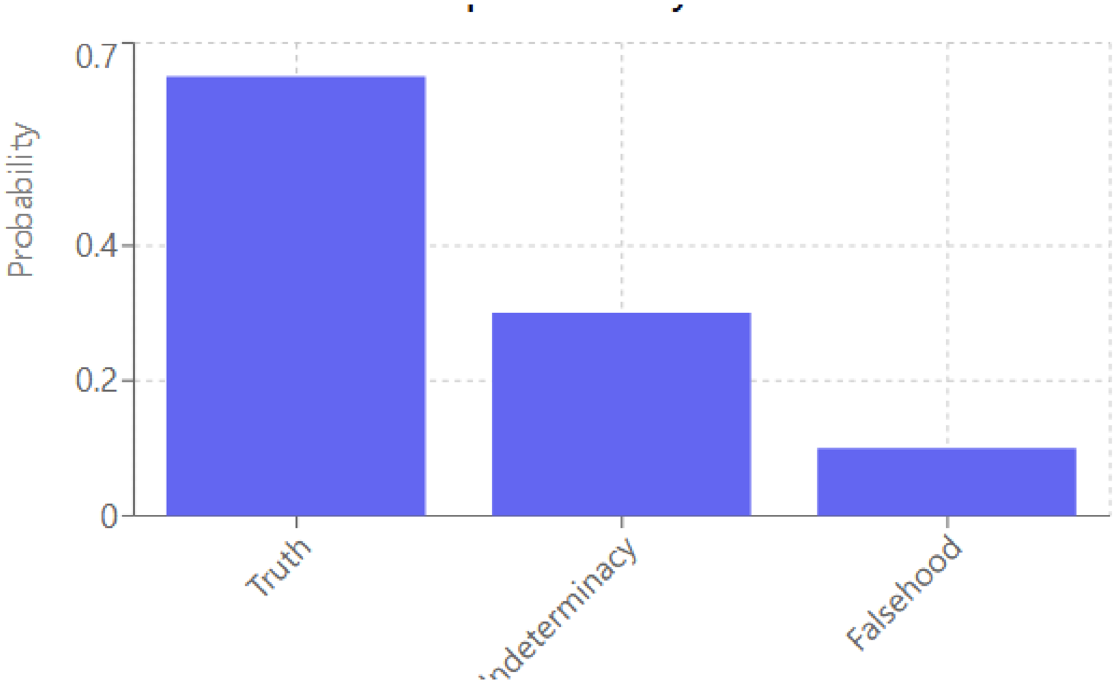

Chart 2: Visualization of the components of the final UNP

g. Analysis of the Validity of the General Hypothesis

The result $UNP = (0.65, 0.30, 0.10)$is interpreted as follows:

- **Degree of Truth (T = 0.65):** There is **65%** evidence or consensus in the scientific literature supporting the hypothesis. This is a moderately high value, suggesting that the hypothesis is plausible and well-founded.
- **Degree of Indeterminacy (I = 0.30):** There is **30%** uncertainty, ambiguity, or lack of consensus. This indicates that there are aspects of the hypothesis that are not fully resolved or for which the evidence is inconclusive.
- **Degree of Falsehood (F = 0.10):** There is **10%** evidence that contradicts the hypothesis. This is a low value, indicating that there are few direct objections or refutations to the general proposition.

The hypothesis is considered to be **more true than false and more indeterminate than false** . The significant presence of indeterminacy requires further analysis to identify its sources.

4. Discussion

The results $UNP = (0.65, 0.30, 0.10)$,offer a nuanced view of the feasibility and challenges of applying AI and neutrosophic models to multigrade literacy pedagogy. The **65% degree of truth** validates the fundamental premise: the integration of systematic, automated data analysis has considerable potential to improve teaching. This aligns with current trends in education that advocate for evidence-based practices.

However, the most revealing component of this analysis is the **high degree of indeterminacy (30%)** . Tracing its origin, we observe that this value comes from the question$Q4$ ($I_4 = 0.30$): *Do neutrosophic plithogenic models adequately capture the uncertainty of educational environments?* This suggests that the main source of doubt lies not in the ultimate goal (improving teaching), but in the suitability and

acceptance of the specific methodological tool (neutrosophic models). The academic and pedagogical community may harbor reservations or simply lack sufficient studies to validate the application of this highly specialized theoretical framework in the field of education.
10% falsity rate , while low, stems from the question $Q3$ ($F_3 = 0.10$): *Are no-code AI tools robust enough to validate complex educational hypotheses? This reflects a minority but existing skepticism about whether "no-*code " platforms possess the necessary rigor for scientific research, compared to solutions that require expert programming and customization.
Taken together, the results do not refute the hypothesis, but rather qualify it. They show that, while the direction is promising, the path involves navigating considerable methodological uncertainty and mild technological skepticism. For educators or educational policymakers, this means that adopting these tools can be beneficial, but it must be done with a critical eye, recognizing that the validation of these methods in the educational field is still underway.

5. *Conclusion*

The plithogenic neutrosophic likelihood analysis determined that the general hypothesis about improving multigrade literacy instruction through AI and neutrosophic models has a univariate likelihood of ($T = 0.65, I = 0.30, F = 0.10$).This result indicates majority support for the hypothesis, but highlights an important area of uncertainty that needs to be addressed.

Practical Implications

The findings suggest that educators and administrators have a solid foundation to explore the use of automated validation tools. The high probability of accuracy (65%) justifies investment in pilot projects. However, the 30% uncertainty cautions against uncritical implementation, pointing to the need for teacher training and ongoing evaluation of the method's effectiveness.

Contributions and Limitations

This study successfully demonstrates how the plithogenic framework can quantify the validity of a complex pedagogical hypothesis, explicitly addressing uncertainty. Its main contribution is to offer a model that goes beyond a simple acceptance or rejection, providing a detailed map of points of consensus, doubt, and dissent. The main limitation, inherent to the simulation, is that the input data are based on a hypothetical sentiment analysis. Furthermore, the high degree of indeterminacy reflects potential gaps in the current academic literature that the method itself helps to highlight.

Recommendations for Future Research

It is recommended to focus future research on the areas that generate the most uncertainty and falsity. Specifically, empirical studies are needed that compare the effectiveness of neutrosophic models with other uncertainty management methods in educational contexts. Likewise, it is crucial to conduct comparative analyses on the reliability of "no- code " AI platforms versus programmable tools in pedagogical research. Developing clearer and more accessible methodological frameworks will be key to reducing uncertainty and maximizing the positive impact of technological innovation in education.

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