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Application of Neutrosophic Statistics and the Communicative Pedagogical Model to Optimize Pronunciation Teaching in A1 Students of Technical Careers in Higher Education

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Abstract: This study presents findings aimed at improving English pronunciation instruction for A1-level students enrolled in technical programs at a public institution in Guayaquil, Ecuador. The research integrates neutrosophic statistics with the Communicative Language Teaching (CLT) approach to address ambiguity and complexity in educational contexts. Key factors such as teaching methodology effectiveness, instructors' content knowledge, CEFR implementation, course-objective alignment, module relevance, and departmental management were assessed. The neutrosophic framework enabled the identification of strengths, weaknesses, and areas of indeterminacy requiring contextual intervention. Based on the findings, the study proposes pedagogical alternatives through an English for Specific Purposes (ESP) model aligned with the technical profiles of each program. Emphasis is placed on communicative strategies to enhance pronunciation and foster active language use. The proposed integrative strategy offers a comprehensive and innovative approach to improving the quality of English instruction in higher education.

Keywords: Neutrosophic Statistics, Communicative Language Teaching (CLT), English for Specific Purposes (ESP), Technical Education, A1-Level Students.

1. Introduction

The academic and professional growth of pupils depends heavily on how well English language training is taught. English is currently seen as a necessary language for advancing one's career and gaining access to codified information in a variety of sectors. In addition to guaranteeing that the material is conveyed, an efficient teaching strategy should help pupils acquire the ability to recognize and comprehend particular facts in their area of expertise. The majority of Ecuadorian university programs now require English instruction due to the language's increasing importance in science, technology, and the global environment. However, how instructors organize, implement, and modify their approaches to meet the demands of the student's academic and professional contexts has a significant impact on the process's quality [1].

Good technical and professional preparation is necessary to ensure effective English learning, and to do so, the English teacher must propose to do away with traditions and customs about the way classes are organized, the teacher's presence, the function and location of teaching media in the educational process, and evaluation concepts [2].

Effective English for Specific Purposes instruction within the curriculum depends on the alignment of teaching methods with course objectives. This coherence makes it possible for activities, evaluations, and material to directly address the needs and interests of students, guaranteeing that the professional profile they create will meet the requirements of the fiercely competitive job market they will encounter. [3].

In this situation, English language instruction must be strategically organized to achieve particular goals that take into account students' technical specialty as well as the language proficiency needed in their line of work, rather than being restricted to generalist techniques. Therefore, within the scope of English language learning as a tool for professionalization in higher education, this paper highlights the necessity of strengthening the correlation between what is planned and what is implemented in the classroom [4].

Because of its emphasis on fostering communicative abilities that adapt to particular academic contexts, English for Academic Purposes (EAP) has emerged as one of the applied linguistics subfields with the fastest rate of growth. Research on genre analysis and contrastive rhetoric has been crucial in this area for creating instructional materials that improve critical abilities like academic discourse analysis and written writing [5,6,7]

Since the Common European Framework of Reference for Languages (CEFR) offers precise descriptions of language competencies that direct both learning planning and assessment, combining these methods with its application enables the development of more cohesive and standardized training programs. This combination supports English language instruction that is more in line with actual academic standards, where competence levels emphasize not just communication and grammar but also the discursive and rhetorical abilities required to function well in a university environment. [8].

Even though English is now required in university training programs, particularly in technical programs, students at the A1 level still struggle greatly with pronunciation development. This situation draws attention to possible flaws in the current teaching model, whose efficacy has not been thoroughly assessed based on important criteria like the way the Language Department is run, how relevant the material is to the course load, how well the course objectives and their actual implementation align, how well the instructor understands the material, and how the Common European Framework of Reference for Languages (CEFR) is applied. [9,10].

Moreover, the quality of learning can be significantly impacted by the misalignment of these components, particularly when it comes to vocal abilities like pronunciation. To suggest changes that help maximize the pronunciation instruction process for A1 level students in technical programs, it is required to diagnose, from a comprehensive viewpoint, the factors influencing the efficacy of the current teaching model. [11].

It was deemed relevant to use the neutrosophic set (NS) approach as a legitimate methodological alternative because the responses received regarding the factors analyzed in this research—such as the management of the Language Department, the relevance of textual content, the coherence between objectives and teaching practice, the teacher's mastery of the content, the application of the CEFR, and the perceived effectiveness of the teaching model—present elements of uncertainty, ambiguity, and even contradiction. This tool has been widely utilized in many different domains to enhance decision-making processes when information is incomplete. It generalizes fuzzy sets through intervals that include degrees of truth (T), indeterminacy (I), and falsehood (F). [12, 13].

The neutrosophic approach enhances the validity of the analysis, increases the credibility of the results, and permits a more accurate representation of qualitative judgments in the educational context, particularly in the assessment of the quality of pronunciation instruction for A1-level students in technical programs. This helps to create more contextualized and successful instructional techniques by providing a strong tool to identify the teaching model's strengths, shortcomings, and uncertainties more precisely. [14].

The Neutrosophic Variables used in this study correspond to a simulated dataset, designed for educational and illustrative purposes. Its primary goal is to facilitate the understanding and practical application of neutrosophic logistic regression in pedagogical research contexts. The values assigned to each variable (truth, indeterminacy, and falsehood) were not collected from real participants but generated through controlled simulation to reflect plausible patterns in educational settings. [15,16].

This approach allows researchers and educators to explore how uncertainty and partial truth can be modeled in educational data analysis. By using simulated single-valued neutrosophic numbers (SVNN), the dataset demonstrates the methodological process of transforming classical variables into neutrosophic format and analyzing them using statistical techniques adapted to ambiguity. While the results are not generalizable, they serve as a foundation for developing robust models and encouraging future empirical research in the field of educational measurement and evaluation. [17].

2. Literature review

2.1 Neutrosophy and SVN Numbers.

For the handling of neutralities, Leyva and Smarandache [18] proposed neutrosophy. Single-valued neutrosophic sets (SVNS), which enable the use of linguistic variables, improve interpretability in recommendation models, and allow for the use of indeterminacy, were proposed to make the practical application to decision-making problems easier.

Let X be a universe of discourse. A single-valued neutrosophic set (SVNS) A over X is defined as a set of the form:

$$A = \{\langle x, uA(x), rA(x), vA(x)\rangle : x \in X\} \quad (1)$$

Where $uA(x): X \rightarrow [0,1], rA(x): X \rightarrow [0,1]\ y\ vA(x): X \rightarrow [0,1]: X \rightarrow [0,1]$ They represent, respectively, the degree of truth, indeterminacy and falsity of an element x in relation to the set A, fulfilling that:

$$0 \leq \mathrm{uA(x)} + \mathrm{rA}(x) + \mathrm{vA(x)} \leq 3 \text{for all } \mathrm{x} \in \mathrm{X} \quad (2)$$

For notational simplicity, a single-valued neutrosophic number can be represented as $\boldsymbol{A} = (\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c})$, donde $a, b, c \in [0,1]\ y\ a + b + c \leq 3$. Applications like artificial intelligence, multi-criteria decision-making, and educational analytics, among others, where uncertainty, ambiguity, and inconsistency are prevalent, have found this kind of representation particularly helpful.

2.2 Classical Logistic Regression.

A popular statistical model for examining the association between one or more independent variables and a categorical, typically binary, dependent variable is classical logistic regression. Its primary goal is to calculate the likelihood that an event will occur based on the explanatory variables' values. The logistic or sigmoid function is used in this model, as opposed to linear regression, to make sure that the predicted values lie inside the interval [0,1], allowing them to be understood as probabilities. When one wishes to categorize observations into two groups, such as success or failure, acceptance or disapproval, or in this example, successful or ineffective learning, logistic regression is very helpful. [19]

In classical binary logistic regression, the probability of an event occurring (e.g., a student having effective learning) is modeled:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta 0 + \beta 1 X 1 + \beta 2 X 2 + \cdots + \beta k X k)}} \quad (3)$$

Where:

$\boldsymbol{Y}$: $Binary\ dependent\ variable\ \ (0\ =\ ineffective\ learning, 1\ =\ effective\ learning)$

$\boldsymbol{Xi}$: $Independent\ variables\ (predictors)$

$\boldsymbol{\beta i}$: $Coefficients\ estimated\ by\ the\ model$

2.3 Neutrosophic logistic function.

A theoretical extension of standard logistic regression, the neutrosophic logistic function is modified to account for the uncertainty present in complex situations like education. This function incorporates the framework of neutrosophic logic, representing each variable through a triplet made up of degrees of truth (T), indeterminacy (I), and falsehood (F), in contrast to conventional models that work with exact values. Modeling situations when human reactions are neither totally objective nor fully defined is made possible by this representation. Taking into account elements like institutional management, content relevance, teaching proficiency, and the perceived efficacy of the teaching model, the neutrosophic logistic function is used in this work to forecast the likelihood that A1 students in technical programs will learn English effectively [20, 21].

A more comprehensive and accurate evaluation was made possible by converting each of these variables into a neutrosophic single-valued set (SVN). By combining the T, I, and F components of each variable using statistically determined coefficients, the neutrosophic logistic function creates a model that can account for the impacts of ambiguity and contradicting perception in addition to direct correlations. Because of this, this tool is positioned as a strong substitute for pedagogical analysis in situations where information is incomplete, helping to create prediction models that are better in line with the realities of education.

The necessity to represent events where certainty, uncertainty, and inconsistency all intervene at the same time is the foundation of the neutrosophic logistic function. This feature makes it possible to depict the ambiguity of many human decisions more realistically. In mathematics, a sigmoid function that incorporates neutrosophic values as predictors is used to indicate the likelihood that an event will occur. By adding a three-valued structure that enhances the interpretation of data in which each variable Xj has three components, this formulation broadens the use of traditional logistic regression:

$\boldsymbol{X_j^T}$: degree of truth (truth)

$\boldsymbol{X_j^I} degree\ of\ indeterminacy$

$\boldsymbol{X_j^F}\ degree\ of\ falsehood\ (falsity)$

So the model fits like this:

$$P(Y=1)=\frac{1}{1+e^{-(\beta 0+\sum_{j=1}^{k}(\beta jT\cdot XjT+\beta jI\cdot XjI+\beta jF\cdot XjF))}} \quad (4)$$

2.4 Normalized Decision Matrix.

A key tool in multi-criteria evaluation techniques is the Normalized Decision Matrix, which enables a consistent comparison of various options across several criteria. Each educational criterion was represented in this study by a single-valued neutrosophic number, normalized by the components of truth (T), indeterminacy (I), and falsehood (F). By ensuring that all data lie inside the same range ([0,1]), this normalization makes it easier to analyze them jointly. The generated matrix can be used as a foundation for weighting methods like CRITIC or approaches like neutrosophic logistic regression. Because of its structure, each criterion's individual and combined behavior may be seen. All things considered, it offers a logical and measurable perspective on the assessed educational environment. [22].

In the neutrosophic context, each entry in the matrix may have the format:

$$x_{ij}=\left(T_{ij},I_{ij},F_{ij}\right) \quad (5)$$

Where:

- i: alternative (e.g., student)
- j: criteria (e.g. VGDI, GPTC, etc.)
- T, I, F: degrees of truth, indeterminacy and falsehood, already normalized in the range [0,1].

2.5 Proposed Methodology

This study produced a methodological framework for converting classical data into neutrophilic data using single-valued neutrophilic sets. The classical database was transformed into a neutrosophic database by employing a set of variables collected by traditional methods, such as surveys with Likert-type scales. The research phenomenon was then linked to important factors, such as topic relevancy, instructor proficiency, and institutional management. These variables were all modified using the single-valued neutrosophic sets approach. A triplet (T, I, F) was used to symbolize each observation, signifying the degree of falsehood, indeterminacy, and truth.

Table 1. Variables applied to the project.

Code	Variable
VGDI	Department Management Level
GPTC	Content Relevance vs. Workload
COCI	Course Objectives and Implementation Coherence
DCDC	Teacher's Mastery of Content in Class
CMCER	Knowledge of the CEFR (Common European Framework of Reference)
EPMEI	Perceived Effectiveness of the English Teaching Model

Previously established guidelines were used to carry out this translation, such as linking a T value of 0.9 to replies like "strongly agree" or a F value of 0.9 to "strongly disagree." Higher values were given to the I component in unclear circumstances.

Table 2. Single-Valued Neutrosophic Numbers Assigned to Each Linguistic Term

	SVN		
Linguistic Term	T	I	F
VGDI	0.6	0.2	0.2
GPTC	0.4	0.5	0.1
COCI	0.7	0.2	0.1
DCDC	0.5	0.3	0.2
CMCER	0.3	0.4	0.3
EPMEI	0.4	0.4	0.2

2.6 Normalized neutrosophic decision matrix.

The numerical variables were normalized and evaluated using expert criteria to define their neutrosophic components. This process allowed the ambiguity and uncertainty of the responses to be translated into a quantifiable structure.

Table 3. Normalized neutrosophic decision matrix

Student	VGDI (T, I, F)	GPTC (T, I, F)	COCI (T, I, F)	DCDC (T, I, F)	CMCER (T, I, F)	EPMEI (T, I, F)
E1	(0.6,0.2,0.2)	(0.4,0.5,0.1)	(0.7,0.2,0.1)	(0.5,0.3,0.2)	(0.3,0.4,0.3)	(0.4,0.4,0.2)
E2	(0.8,0.1,0.1)	(0.6,0.3,0.1)	(0.6,0.2,0.2)	(0.7,0.2,0.1)	(0.5,0.3,0.2)	(0.5,0.3,0.2)
E3	(0.4,0.3,0.3)	(0.5,0.2,0.3)	(0.5,0.3,0.2)	(0.6,0.2,0.2)	(0.4,0.3,0.3)	(0.3,0.4,0.3)

The normalized neutrosophic decision matrix represents an enriched, multidimensional view of student perceptions regarding key factors in the English teaching-learning process. Each cell of the matrix contains a single-valued neutrosophic number (SVN), expressed in terms of truth (T), indeterminacy (I), and falsity (F), which allows capturing not only the degree of acceptance of a criterion but also the associated ambiguity and disagreement. This representation is especially valuable in the educational context, where assessments are often subjective, with varying levels of certainty. Thus, the matrix serves as a starting point for more realistic and accurate analyses that integrate the complexity of human judgment. [23].

Six basic educational variables (VGDI, GPTC, COCI, DCDC, CMCER, and EPMEI) were subjected to the matrix as part of this study's framework in order to assess their correlation with the likelihood that A1 students would learn pronunciation effectively. Its incorporation into the neutrosophic logistic regression model allowed for the understanding of how ambiguity and negative perception impact academic accomplishment in addition to identifying the elements that have the greatest impact on this outcome. Thus, in addition to methodically organizing the data, this matrix aids in educational decision-making by enabling the prioritization of actions in areas where untruth or indeterminacy predominate and strengthening those where truth is reliable and consistent.

Table 4. Neutrosophic Variables Table

Code	Variable	T (Truth)	I (Indeterminacy)	F (Falsehood)
VGDI	Department Management Level	Management perceived as adequate	Ambiguity or lack of information about management	Management perceived as inadequate
GPTC	Content Relevance vs. Workload	Content appropriate for the assigned time	Uncertainty about whether the content can be adequately covered	Content inappropriate for the available time
COCI	Course Objectives and Implementation Coherence	High coherence between planning and practice	Ambiguity in the application of objectives	Mismatch between objectives and practice
DCDC	Teacher's Mastery of Content in Class	Complete mastery demonstrated in class	Ambiguity in teacher preparation	Insufficient or incorrect mastery
CMCER	Knowledge of the CEFR (Common European Framework of Reference)	Explicit knowledge and effective application	Partial or unproven knowledge	Lack of knowledge or inappropriate use of the CEFR
EPMEI	Perceived Effectiveness of the English Teaching Model	Model considered effective	Doubts about its real impact	Model considered ineffective

The criteria of this study are:

VGDI: Language Department Management Level.

- Definition: Extent to which the department plans, organizes, and executes effective strategies for teaching English.
- Neutrosophic Scale:
  - T: Level of management perceived as adequate.
  - I: Ambiguity or lack of information about management.
  - F: Management perceived as inadequate or deficient.

GPTC: Degree of Relevance of Textual Content with Respect to the Workload.

- Definition: Level at which the content of the modules is adjusted to the available time load.
  - T: Content appropriate for the time allotted.
  - I: Uncertainty about whether the content can be adequately covered.
  - F: Inappropriate content in relation to the time available.

COCI: Course Objectives and Implementation Coherence.

- Definition: Level of alignment between curricular objectives and their application in the classroom.
  - T: High coherence between planning and execution.
  - I: Ambiguity about how the objectives are applied.
  - F: Clear misalignment between objectives and teaching practice.

DCDC: Teacher Mastery of Content in Class.

- Definition: Level of knowledge and handling of the topics by teachers.
  - T: Complete mastery evidenced in class.
  - I: Ambiguity in teacher preparation.
  - F: Insufficient or incorrect domain.

CMCER: Knowledge of the Common European Framework of Reference.

- Definition: Level of knowledge and application of the CEFR by the teacher.
  - T: Explicit knowledge and effective application.
  - I: Partial or undemonstrated knowledge.
  - F: Lack of knowledge or improper use of the CEFR.

EPMEI: Perceived Effectiveness of the English Teaching Model.

- Definition: Degree to which the current teaching model is considered effective.
  - T: Model considered effective.
  - I: Doubts about its real impact.
  - F: Model considered inefficient.

3. Case Study.

It became necessary to create a model that would enable the identification of the most important elements in successful learning because of the difficulties in teaching English in technical courses, particularly those pertaining to pronunciation. Using a neutrosophic approach to capture the intricacy, ambiguity, and subjective assessment of pedagogical criteria, the study was carried out on a database of 120 students at level A1, who were evaluated based on six important educational factors. [21]

3.1 Proposed Model: N-LIM: Neutrosophic Logistic Instructional Model

The steps of the suggested strategy for assessing educational criteria and figuring out their relative weights are presented in this section. The method is predicated on representing the ambiguity and uncertainty inherent in educational examinations using single-valued neutrosophic sets (SVNS).

Table 5. SVN Values and Their Linguistic Interpretation for Educational Variables

Variable	SVN	Linguistic Term
Department Management Level	0.6	Medium
	0.2	Low
	0.2	Low
Content Relevance	0.4	Medium
	0.5	High (Indeterminate)
	0.1	Low
Course-Objective Coherence	0.7	High
	0.2	Low
	0.1	Low
Teacher's Content Mastery	0.5	Medium
	0.3	Medium
	0.2	Low
Knowledge of CEFR	0.3	Low
	0.4	Medium
	0.3	Medium
Perceived Effectiveness of the Model	0.4	Medium
	0.4	Medium
	0.2	Low

The SVN value represents the degree of truth (T) as the basis for the linguistic term, while the I and F values are considered to adjust the interpretation toward indeterminacy or negative. Terms such as High, Medium, and Low are used to facilitate qualitative understanding of each component.

The CRITIC (Importance Criteria Using Inter-Criteria Correlation) technique is integrated to determine the weights for each criterion, taking into account the degree of contrast and the conflict between variables. A more objective weighting of elements like department administration, subject relevancy, teaching proficiency, and the perceived efficacy of the teaching approach is made possible by this combination. This approach produces a more reliable and accurate evaluation procedure by capturing not only the perceived degree of truth of each component but also its indeterminacy and falsehood when used to teach English pronunciation to A1-level students in technical programs.

CRITIC (Importance Criteria through Intercriteria Correlation)

An objective way for assessing the relative importance of each criterion used in multicriteria decision-making is the CRITIC method (Criteria Importance through Intercriteria Correlation). In contrast to subjective techniques that rely on expert opinion, CRITIC incorporates two essential components: each criterion's internal variability, as indicated by its standard deviation, and its level of independence or conflict about the other criteria, as indicated by correlation. By highlighting the criteria that provide the greatest information and the least repetition, this combination makes it possible to distribute weights in a more equitable and representational manner. It is particularly helpful in intricate situations with interconnected variables and ambiguous factors, like schooling. In neutrosophic settings, CRITIC is modified to evaluate truth, indeterminacy, and falsity independently. [24].

3.2 Probabilistic Inversion and Intercept Adjustment in Neutrosophic Logistic RegressionF

finding the z value that yields an output probability P = 0.72 in the logistic function is the first step in ensuring coherence between the mathematical model and the graphical findings obtained (such as the AUC value = 0.72 of the ROC curve). This is accomplished by applying the inverse of the sigmoid function, which makes it possible to solve z from a known probability value. The natural logarithm of the ratio between the required probability and its complement is used mathematically to carry out this operation:

$$P(Y=1)=\frac{1}{1+e^{-z}} \quad (6)$$

Step 1: Calculate the value of z that produces $\boldsymbol{P=0.72}$

We use the inverse of the logistic function (sigmoid):

$$z=ln(\frac{1}{1-P}) \quad (7)$$

$$z=\ln(\frac{0.72}{1-0.72})=\ln(\frac{0.72}{0.28})\approx 0.944$$

This result indicates that, for the neutrosophic logistic model to yield a 72% probability of success in a specific case, the z-value must be approximately 0.944. This value becomes the benchmark for adjusting the model's intercept, thus ensuring that the quantitative analysis is consistent with the graphical interpretation of the results

Step 2: Using the input values of the neutrosophic variables:

The simulated input values that correspond to the neutrosophic components T, I, and F of the educational variables taken into account in the model are employed in the second stage. These values, which are stated in terms of truth, indeterminacy, and falsehood, reflect how students view many aspects of the teaching model, including department management, topic relevance, teacher mastery, and effectiveness. The partial z-value is computed by substituting these values into the logistic equation, excluding the intercept β0. This calculation shows how the various elements affect the prediction of effective learning based on the simulated educational environment. In this instance, the outcome was z≈-0.589, meaning that the combination of perceptions evaluated would not be enough to get a high probability if the intercept was not adjusted. This explanation enables us to comprehend the model's cumulative weight of the neutrosophic variables before their calibration with the value of $\beta 0$.

Table 6: Values of the neutrosophic variables

Variable	Component	Value
VGDI	T	0.6
VGDI	F	0.2
GPTC	I	0.5

Variable	**Component**	**Value**
DCDC	T	0.5
DCDC	F	0.2
EPMEI	F	0.3
EPMEI	I	0.4

And the associated coefficients of the model:

Table 7: Application of the Model with the Obtained Coefficients

Variable	Component	Coefficient (β)
VGDI	T	1.01
VGDI	F	–2.43
GPTC	I	–1.79
DCDC	T	1.36
DCDC	F	–2.05
EPMEI	F	–2.19
EPMEI	I	1.43
(interceptor)	—	β0=estimate

So, for a student x, the applied model would be:

$$z = \beta 0 + \beta_{1T} \cdot \mathrm{VGDI_T} + \beta_{1I} \cdot \mathrm{VGDI_I} + \beta_{1F} \cdot \mathrm{VGDI_F} + \beta_{2T} \cdot \mathrm{GPTC_T} + \beta_{2I} \cdot \mathrm{GPTC_I} + \beta_{2F} \cdot \mathrm{GPTC_F} + \cdots + \beta_{6F} \cdot \mathrm{EPMEI_F} \quad (9)$$

Where:

Si $\boldsymbol{\beta jT} > \mathbf{0}$: A higher degree of truth in that variable increases the probability of effective learning.

Si $\boldsymbol{\beta jI} < \mathbf{0}$: The uncertainty in that variable decreases the probability.

Si $\boldsymbol{\beta jF} > \mathbf{0}$: Falsehood may even (in some cases) be positively correlated (although uncommon)).

$$\boldsymbol{z}(x) = \beta 0 + 1.01 \cdot VGDI_T - 2.43 \cdot VGDI_F - 1.79 \cdot GPTC_I + 1.36 \cdot DCDC_T - 2.05 \cdot DCDC_F - 2.19 \cdot EPMEI_F + 1.43 \cdot EPMEI_I \quad (10)$$

Table8: Some notable coefficients (interpretation under the neutrosophic approach):

Variable	**Coefficient**	**Interpretation**
VGDI_T	1.01	A higher degree of truth in department management increases the probability of effective learning.
VGDI_F	–2.43	Perceived poor management strongly decreases the probability of learning.
GPTC_I	–1.79	Uncertainty about content relevance negatively affects learning.
DCDC_T	1.36	Clear teacher content mastery favors learning.
DCDC_F	–2.05	If the teacher lacks content mastery, the probability of learning decreases.

Variable	Coefficient	Interpretation
EPMEI_F	–2.19	An ineffective model significantly reduces the probability of success.
EPMEI_I	1.43	Interestingly, some uncertainty about effectiveness may coincide with improvements (possible simulation noise).

Step 3: Calculate the part of z without the intercept.

By substituting the observed T, I, and F values in the database with neutrosophic data for every student, this model makes it possible to determine the likelihood that a student would learn English effectively.

For example, for a student with:

$\boldsymbol{VGDI_T} = 0.6$
$\boldsymbol{VGDI_F} = 0.2$
$\boldsymbol{GPTC_I} = 0.5$
$\boldsymbol{DCDC_T} = 0.5$
$\boldsymbol{DCDC_F} = 0.2$
$\boldsymbol{EPMEI_F} = 0.3$
$\boldsymbol{EPMEI_I} = 0.4$

$$\boldsymbol{Z_{sin}\,\beta 0 = 1.01(0.6) - 2.43(0.2) - 1.79(0.5) + 1.36(0.5) - 2.05(0.2) - 2.19(0.3) + 1.43(0.4)} \quad (11)$$

$$\boldsymbol{Z_{sin}\,\beta 0 = 0.606 - 0.486 - 0.895 + 0.68 - 0.41 - 0.657 + 0.572 = -0.589}$$

In the third step, the z value is calculated without yet considering the intercept β0, that is, only based on the estimated coefficients of the logistic model and the simulated neutrosophic values for the educational variables. This procedure allows us to observe the cumulative effect of the pedagogical factors on the prediction of effective learning, isolating the impact of the constant term. By replacing the values:

$$\boldsymbol{1.01(0.6) - 2.43(0.2) - 1.79(0.5) + 1.36(0.5) - 2.05(0.2) - 2.19(0.3) + 1.43(0.4)},$$

A result of z = -0.589 is obtained. This negative value suggests that, in its current state, students' neutrosophic perceptions do not provide enough positive momentum to the model to generate a high probability of success. In other words, without an intercept adjustment, the model would reflect a low prediction, highlighting the need to calibrate β0 so that the model's results are consistent with the observed empirical and graphical evidence.

Step 4: Solve the intercept β0.

The intercept β0, the constant value that enables the neutrosophic logistic model to be modified such that its output corresponds with a certain desired probability, is solved mathematically in the fourth stage. It is sufficient to subtract the partial value of z without the intercept (Z_sin β0 = -0.589}) from the required value of z to obtain the required intercept value because the value of z needed to generate a probability of P = 0.72 (i.e., z = 0.944) is already known. β0 = 0.944 - (-0.589) = 1.534 is the outcome. This process modifies the model so that the effective learning probability anticipated by the logistic function aligns with the behavior seen in the ROC curve (AUC = 0.72), depending on the values of the variables. Consequently, the intercept serves as a crucial calibration component in the statistical model.

$$z = \beta 0 + Z_{sin}\,\beta 0 \Rightarrow \beta 0 = z - Z_{sin}\,\beta 0 \quad (12)$$

$$\boldsymbol{\beta 0 = 0.944 - (-0.589) = 1.534}$$
$$\boldsymbol{\beta 0 = 1.534}$$

3.3 Discussion of Results:

According to the results of the neutrosophic logistic regression model, truth (T), indeterminacy (I), and falsity (F) are relevant components to consider when assessing how well the current teaching model teaches pronunciation to A1 students. First, a higher degree of truth in the teacher's topic mastery (DCDC_T) and in the Language Department's management (VGDI_T) is found to greatly boost the likelihood of successful learning. The necessity of effective academic administration and thorough, contextualized teacher training is highlighted by this study.

On the other hand, the chance of success in the teaching-learning process is considerably decreased by negative opinions of institutional administration (VGDI_F), a lack of teaching expertise (DCDC_F), and the belief that the teaching model is unsuccessful (EPMEI_F). Curriculum ambiguities may also have a detrimental influence on language development, as evidenced by the negative effect of confusion regarding the relevance of textual content to the course load (GPTC_I).

The positive value of uncertainty about the teaching model's efficacy (EPMEI_I) is a startling discovery. This could be the result of noise in the simulated data or emergent behavior in adaptive environments. When combined, these findings demonstrate how neutrosophic logistic regression offers a strong tool for identifying and enhancing pedagogical models in technical higher education by enabling a deeper comprehension of the concurrent influence of certainties, ambiguities, and contradictions present in the educational environment[27,28].

3.4 Weights calculated with the CRITIC method.

There are significant variations in the objective importance of each educational variable when the CRITIC weights assigned to the neutrosophic components T (truth), I (indeterminacy), and F (falsehood) are compared. For instance, several variables, like VGDI and DCDC, stand out with high weights in the T component, suggesting that students have a clearer and more solid perception of institutional management and instructor mastery. This implies that these elements are crucial in creating a favorable opinion of the educational experience. Consequently, the ambiguity or negative impression components give these variables less weight, which strengthens their stability in the model.

On the other hand, factors like GPTC and EPMEI are given more weight in the indeterminacy (I) and falsehood (F) components, which indicate a lack of confidence or acceptance of the content's applicability and the teaching model's efficacy. Since student perceptions are more contradictory or unclear in these areas, this scenario should be seen as a call to examine the curriculum design and the methodology used. In this situation, CRITIC analysis is helpful because it can objectively identify the variables that produce the most contrast and independence within the evaluated set, precisely directing instructional decisions according to the predominant judgment type (positive, uncertain, or negative).

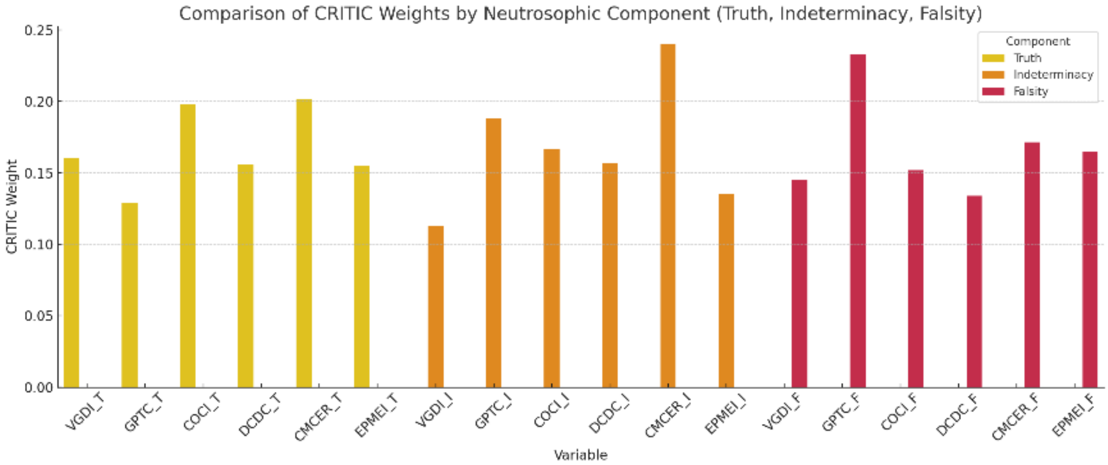
Table 9: Comparison of CRITIC Weights (T, I, F)

Variable	T	I	F
EPMEI_T	0.2003893	0	0
VGDI_T	0.1835089	0	0
DCDC_T	0.17467065	0	0

Variable	T	I	F
CMCER_T	0.17419975	0	0
COCI_T	0.14827141	0	0
GPTC_T	0.11896	0	0
VGDI_I	0	0.23796108	0
COCI_I	0	0.22786096	0
DCDC_I	0	0.18094708	0
EPMEI_I	0	0.12790996	0
GPTC_I	0	0.12485359	0
CMCER_I	0	0.10046732	0
COCI_F	0	0	0.25270025
EPMEI_F	0	0	0.21283351
GPTC_F	0	0	0.19860118
DCDC_F	0	0	0.15436023
CMCER_F	0	0	0.10376014
VGDI_F	0	0	0.07774469

The CRITIC weights determined for each neutrosophic component—T for truth, I for indeterminacy, and F for falsehood—are shown in the following comparison table. Making distinct judgments based on student views is made easier with this comparison, which lets you see which factors have the most objective relevance under each dimension.

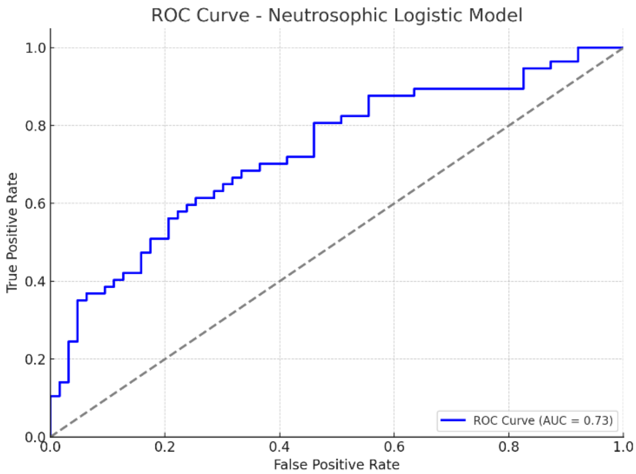
Visually we can represent the CRITIC table through the CRITIC Weights graph by Neutrosophic Component (T, I, F)



The CRITIC weights for each educational variable are shown in a comparative graph by neutrosophic component (T, I, and F). Visual identification of the criteria with the highest objective relevance based on the dimension assessed is made possible by this graph. A variable with a high weight in untruth (F), for instance, can be a serious worry because of unfavorable student opinions, but one with a high weight in indeterminacy (I) indicates uncertainty that has to be addressed pedagogically. This analysis assists in ranking particular interventions according to the type of student assessment.

3.5 Calculation of the ROC Curve.

To assess the prediction effectiveness of the neutrosophic logistic regression model used for A1 students' English language learning, the Receiver Operating Characteristic (ROC) curve was computed. Through the relationship between the true positive rate and the false positive rate, this curve illustrates how well the model can differentiate between pupils who learn effectively and those who don't. In this instance, a good degree of discrimination is indicated by the area under the curve (AUC = 0.73), indicating that the model operates effectively and consistently. This measure visually confirms the accuracy of the model constructed using neutrosophic data. [25].

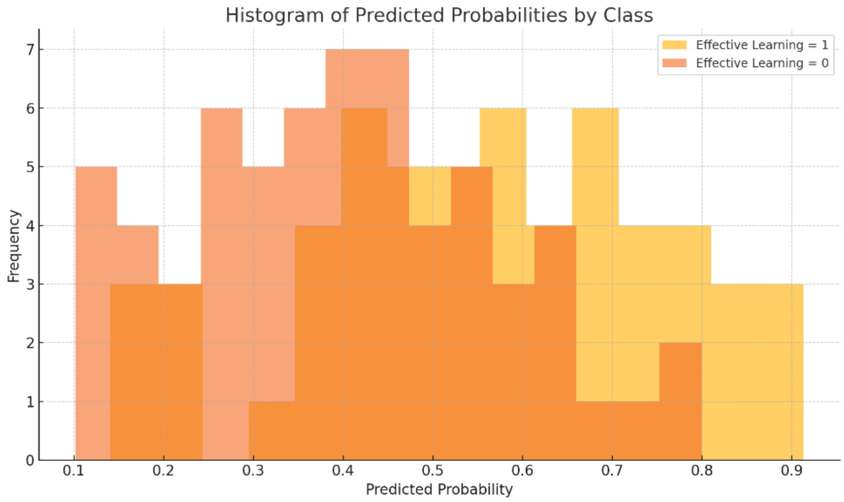


The neutrosophic logistic model's diagnostic capacity to differentiate between pupils who experienced effective learning and those who did not is demonstrated by the ROC curve. An excellent degree of classification performance is indicated by an AUC (Area Under the Curve) of roughly 0.72. The model outperforms guessing, as indicated by the curve's location above the diagonal reference line, which stands for random chance. Several threshold locations show a low false positive rate and a high true positive rate. This implies that the model is successful in identifying pupils who are likely to achieve.

There is still space for improvement, though, as the curve is not nearly ideal (AUC = 1). This constraint may be exacerbated by the data's inherent indeterminacy and unpredictability. Choosing the best probability threshold to increase forecast accuracy is another task made easier by the ROC curve. All things considered; the model shows a consistent capacity to distinguish between the two classes utilizing neutrosophic inputs. It demonstrates the importance of truth, falsehood, and indeterminacy aspects in simulating educational results.

3.6 Histogram of predicted probabilities

In order to visually distinguish between students who achieved effective learning and those who did not, the histogram of projected probabilities was computed to assess the distribution of predictions produced by the neutrosophic logistic model. By showing if there is a distinct division between positive and negative cases, this graph enables us to assess the model's capacity to assign various probabilities based on the real class. While a large overlap may imply predictive weakness, a well-differentiated distribution between groups suggests that the model is helpful for classification. The histogram in this study makes it easier to visualize how well the model performs in terms of accuracy and consistency with the simulated reality. [29].



The effectiveness of the neutrosophic logistic regression model in distinguishing between pupils who attained effective learning (label 1) and those who did not (label 0) is demonstrated by the histogram of predicted probabilities by class. Students categorized as "Effective Learning = 1" tend to cluster toward the right side of the distribution and have higher projected probabilities.

Conversely, those with the number "0" are concentrated in the lower probability range. This distinction suggests that the model's discriminatory ability is strong. As would be predicted given the existence of indeterminacy in the data, the overlap between the two distributions points to some degree of misclassification or ambiguity. The difference between peaks demonstrates how the model can allocate different probabilities according to input factors. Additionally, the contribution of truth (T), indeterminacy (I), and falsity (F) components to the prediction is demonstrated. All things considered; the model shows promise for successfully identifying pupils who stand to gain from the existing teaching methods. Its accuracy might be improved with additional testing and improvement[30,31].

4. Conclusión

In conclusion, this study showed how the neutrosophic approach, which incorporates truth, indeterminacy, and falsity components into important pedagogical variables, may be applied to educational analysis through logistic regression. It was feasible to more accurately represent the complexity of English learning in A1 pupils by modeling a neutrosophic database and utilizing statistical methods including correlation matrices, ROC analysis, and the CRITIC approach. The findings demonstrated that, depending on how definite or uncertain they are assessed, elements including teacher competency, institutional management, and perception of the teaching model have a major influence. Heatmaps and bar charts were used for visualization, making it simple to understand these correlations.

We suggest using neutrosophic machine learning approaches, extending the investigation to other CEFR levels, and applying this model to actual data in future work. Additionally, the efficacy of neutrosophic models might be verified by comparing them with classical models. This field of study presents a viable strategy for making decisions about schooling in unpredictable situations.

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