Neutrosophic Sets and Systems, Vol. 70, 2024
University of New Mexico

Assessment of three strategies for teaching an AI literacy program, based on a neutrosophic 2-tuple linguistic model hybridized with the ARAS method

Víctor Gustavo Gómez-Rodríguez [1], Raidell Avello-Martínez [2], Tomasz Gajderowicz [3], Noemí Bárbara Delgado Álvarez [4], Johanna Irene Escobar Jara [5], Noel Batista Hernández [6], Segress García Hevia [7], Daniel D. Iturburu Salvador [8]

[1] Universidad Bolivariana del Ecuador (UBE), km 5.5 Vía Durán, Guayas, Ecuador. Email: vgomez@ube.edu.ec
[2] Universidad Bolivariana del Ecuador (UBE), km 5.5 Vía Durán, Guayas, Ecuador. Email: ravellom@ube.edu.ec
[3] Departamento de Economía de la Educación y la Labor, Universidad de Varsovia, Polonia. Email: tgajderowicz@wne.uw.edu.pl
[4] Universidad Bolivariana del Ecuador (UBE), km 5.5 Vía Durán, Guayas, Ecuador. Email: ndelgadoa@ube.edu.ec
[5] Universidad Bolivariana del Ecuador (UBE), km 5.5 Vía Durán, Guayas, Ecuador. Email: jescobarj@ube.edu.ec
[6] Universidad Bolivariana del Ecuador (UBE), km 5.5 Vía Durán, Guayas, Ecuador. Email: nbatistah@ube.edu.ec
[7] Universidad de Guayaquil (UG), Ciudadela Universitaria, Guayaquil, Guayas, Ecuador. Email: segress.garciah@ug.edu.ec
[8] Universidad de Guayaquil (UG), Ciudadela Universitaria, Guayaquil, Guayas, Ecuador. Email: douglas.iturburus@ug.edu.ec c

Abstract. This study analyzes some general Artificial Intelligence competency frameworks, aimed at teachers, and it proposes a comprehensive Artificial Intelligence literacy training program, designed to develop in university teachers the necessary skills to integrate Artificial Intelligence into their curricula and research. Through a mixed theoretical-practical approach, the program addresses the gaps identified in the existing literature. The program covers the foundations of Artificial Intelligence to its specific application in teaching, highlighting ethical aspects, critical thinking, and its integration into pedagogy. Based on frameworks such as DigiComEdu, the program is presented as a strategic response to empower teachers, ensuring their preparation to lead the responsible implementation of AI in the classroom and research. One of the issues to consider is how to apply the program. To this end, there were three options: (1) Teaching classes that are 80% theoretical and 20% practical (2) Teaching classes that are 50% theoretical and 50% practical (3) Teaching classes that are 20% theoretical and 80% practical. For the general evaluation and ranking of each of the program's teaching alternatives, a hybrid method between the neutrosophic 2-tuple linguistic model and the Additive Ratio Assessment System (ARAS) was used. Among the advantages of using this method are the possibility for experts to use natural language in their evaluations, the accuracy of the evaluations as more possible states of knowledge are incorporated, and finally the simplicity in the application of the method.

Keywords: Neutrosophic 2-tuple linguistic model, ARAS method, AI literacy, AI competencies, Artificial Intelligence, AI literacy program, Teacher training.

.

1 Introduction

Artificial intelligence refers to a type of algorithm or computerized systems that imitate human intellectual processes, such as the ability to generalize, reason, discover meaning, and learn from past experiences [1]. The term “artificial” bears a close similarity to the actual mental decision-making processes in human brains. For example, mathematical reasoning and causal reasoning tasks activate an important brain network called the task-positive network, which includes several brain regions associated with attention and cognition.

The significance of Artificial Intelligence (AI) in the university environment is not only limited to the implementation of advanced technologies but also redefines the very nature of research and education. In research, AI has proven to be an invaluable tool, enabling massive data analysis, identifying complex patterns, and accelerating scientific discoveries. In the educational field, AI introduces innovative personalized teaching and learning methods, adapting to the individual needs of students. However, this shift towards integrating AI into education and research poses particular challenges for university educators, who must acquire specialized skills to fully realize the potential of this constantly evolving technology.

Given this panorama, the need arises to comprehensively address AI literacy for teachers, particularly university teachers. Understanding AI competence frameworks is an essential component of empowering educators, allowing them to not only use advanced AI tools but also foster literacy in these new resources among their students. Furthermore, the implementation of a specific training system focused on AI literacy stands as a key strategy to close the gap between the rapid evolution of technology and the effective preparation of university teachers. The present study proposes a training system that empowers teachers to lead effectively in educational environments impacted by AI.

Within the framework of this study, a mixed and non-systematic exploratory methodology has been adopted, guided by the flexibility necessary to address the dynamic, and constantly evolving, nature of the field of artificial intelligence literacy for university teachers. Following the guidelines of the European Framework for the Digital Competence of Educators (DigCompEdu), our approach has focused on the identification and analysis of international initiatives related to AI literacy, specifically focusing on the university context.

Data collection encompassed an exhaustive search of academic websites, social media, educational and scientific databases, as well as digital publishing platforms. This diversified strategy allowed us for a variety of perspectives and approaches to AI literacy. The selection of initiatives was based on perceived relevance and pertinence to the topic of study, prioritizing those with significant scope, notable innovations, or unique approaches to AI literacy.

The data analysis was carried out using a qualitative approach, seeking to identify the artificial intelligence competencies necessary for university teachers. This qualitative exploration sought to outline common trends and strategies, as well as areas of focus within the selected initiatives that relate directly to the development of skills essential for the effective and ethical use of AI. Special attention was given to the competencies that are considered fundamental to train educators in the integration of AI in their pedagogical and research practices. Thus, all of this knowledge collection and analysis yielded to an IA literacy program for teachers.

Specifically, evaluation work is carried out on three possible ways of applying the proposed program to teachers, which in a simplified manner are differentiated into (1) Teaching classes that are 80% theoretical and 20% practical (2) Teaching classes that are 50% theoretical and 50% practical (3) Teaching classes 20% theoretical 80% practical. A ranking was obtained according to 5 experts of the possible ways of teaching the program based on a new model that appeared in the literature where the neutrosophic 2-tuple linguistic model is hybridized with the Additive Ratio Assessment System (ARAS) decision-making method [2]. The neutrosophic 2-tuple linguistic model is a generalization of the well-known 2-tuple linguistic model, which is a Computing with Words (CWW) method to perform symbolic linguistic operations where no information is lost [3]. The generalization to the neutrosophic framework allows us to obtain greater accuracy in capturing the opinion of the experts, since apart from the opinion on each attribute, there is also the opinion against and the indeterminacy.

ARAS belongs to the series of decision-making methods, which is characterized by its simplicity. It consists of comparing the values of the attributes with a pre-established ideal value [4].

The study is carried out based on an Artificial Intelligence literacy training program that is an adaptation of the DigCompEdu in universities or higher education centers in Latin America. Specifically, it is studied within the campus of the Bolivarian University of Ecuador. Some readings about Neutrosophy applied to Artificial Intelligence and Education can be found in [5-7], for Artificial Intelligence in [8-11], and education in [12, 13].

The paper is divided into a Materials and Methods section with the fundamental notions about the Neutrosophic 2-tuple Linguistic Model, the ARAS method, and the hybrid between both of them introduced in [4]. Section 3 contains the results of evaluating three didactic strategies for applying the proposed AI literacy program using the model explained above. The last section is dedicated to presenting the conclusions.

2 Materials and Methods

2.1 Basic Concepts of Neutrosophic 2-tuple Linguistic Model

Definition 1 ([14-16]). Let $S=\{s_0,s_1,\dots,s_g\}$ be a set of linguistic terms and $\beta\epsilon[0,g]$ is a value that represents the result of a symbolic operation, then the linguistic 2-tuple that expresses the information equivalent to β is obtained using the following function:

$$\Delta:[0,g]\to S\times[-0.5,0.5)$$
$$\Delta(\beta)=(s_i,\alpha) \quad (1)$$

Where s_i is such that $i=\text{round}(\beta)$ and $\alpha=\beta-i,\alpha\in[-0.5,0.5)$ and "round" is the usual rounding operator, s_i is the index label closest to β and α is the value of the symbolic translation.

It should be noted that $\Delta^{-1}:\langle S\rangle\to[0,g]$ is defined as $\Delta^{-1}(s_i,\alpha)=i+\alpha$. Thus, a linguistic 2-tuple $\langle S\rangle$ is identified with its numerical value in $[0,g]$.

Suppose that $S=\{s_0,\dots,s_g\}$ is a *2-Tuple Linguistic Set* (2TLS) with odd cardinality g+1. It is defined for

$(s_T, a), (s_I, b), (s_F, c) \in L$ and a, b, c $\in[0, g]$, where $(s_T, a), (s_I, b), (s_F, c) \in L$ independently express the degree of truthfulness, indeterminacy, and falsehood by 2TLS. *2-Tuple Linguistic Neutrosophic Number* (2TLNN) is defined as follows:

$$l_j = \left\{(s_{T_j}, a), (s_{I_j}, b), (s_{F_j}, c)\right\} \quad (2)$$

Where $0 \le \Delta^{-1}(s_{T_j}, a) \le g$, $0 \le \Delta^{-1}(s_{I_j}, b) \le g$, $0 \le \Delta^{-1}(s_{F_j}, c) \le g$, and $0 \le \Delta^{-1}\left(s_{T_j}, a\right) + \Delta^{-1}\left(s_{I_j}, b\right) + \Delta^{-1}(s_{F_j}, c) \le 3g$.

The scoring and accuracy functions allow us to rank 2TLNN.

Let $l_1 = \left\{(s_{T_1}, a), (s_{I_1}, b), (s_{F_1}, c)\right\}$ be a 2TLNN in L, the scoring and accuracy functions in l_1 are defined as follows, respectively:

$$S(l_1) = \Delta\left\{\frac{2g + \Delta^{-1}(s_{T_1}, a) - \Delta^{-1}(s_{I_1}, b) - \Delta^{-1}(s_{F_1}, c)}{3}\right\}, \Delta^{-1}(S(l_1)) \in [0, g] \quad (3)$$

$$H(l_1) = \Delta\left\{\frac{g + \Delta^{-1}(s_{T_1}, a) - \Delta^{-1}(s_{F_1}, c)}{2}\right\}, \Delta^{-1}(H(l_1)) \in [0, g] \quad (4)$$

2.2 Additive Ratio Assessment System (ARAS)

The first step in solving the multi-criteria decision-making problem with the support of the ARAS method is to create the $m \times n$ following matrix with m feasible alternatives per row evaluated according to n criteria given by columns [4].

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} i = 1,2,\dots,m; j = 1,2,\dots,n. \quad (5)$$

Where m is the number of alternatives, n is the number of criteria that describe each alternative, x_{ij} represents the evaluation of the ith alternative according to the jth criterion, while x_{0j} is the optimal value of the jth criterion.

When the jth criterion is unknown then it is taken:

$$x_{0j} = max_i\, x_{ij}, \text{if } max_i\, x_{ij} \; is\ preferable$$
$$x_{0j} = min_i\, x_{ij}^*, \text{if } min_i\, x_{ij}^* \; is\ preferable \quad (6)$$

The criteria whose values are maximum are normalized with the following Equation:

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad (7)$$

The criteria whose values are minimum are normalized with the following Equations:

$$x_{ij} = \frac{1}{x_{ij}^*}, \bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad (8)$$

In the other stage, the weights w_j are taken for the criteria, where $w_j \in (0,1)$ satisfy:

$$\sum_{j=1}^{n} w_j = 1 \quad (9)$$

Thus, the matrix is obtained:

$$\hat{X} = \begin{bmatrix} \hat{x}_{01} & \cdots & \hat{x}_{0j} & \cdots & \hat{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{i1} & \cdots & \hat{x}_{ij} & \cdots & \hat{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \cdots & \hat{x}_{mj} & \cdots & \hat{x}_{mn} \end{bmatrix} i = 1,2,\dots,m; j = 1,2,\dots,n. \quad (10)$$

This is the matrix with elements normalized by the Equation:

$$\hat{x}_{ij} = \bar{x}_{ij} w_j;\ j = 1,2,\dots,n \quad (11)$$

The values are calculated below:

$$O_i = \sum_{j=1}^{n} \hat{x}_{ij};\ i = 1,2,\dots,m. \quad (12)$$

Where O_i is the value of the optimality function of the alternative i.

The highest value for O_i is the best and the lowest value is the worst.

The degree of usefulness of the ith alternative is obtained by comparing it with the ideal degree O_0, which is obtained according to Equation 13:

$K_i = \frac{O_i}{O_0}; i = 1,2, \dots, m.$ (13)

Figure 1 contains a diagram of the algorithm to follow in the ARAS method.

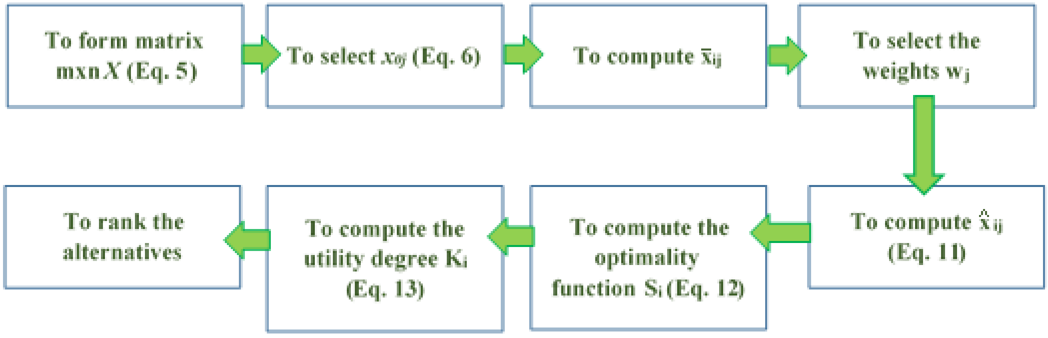

Figure 1: Scheme of the ARAS algorithm for multi-criteria decision-making. Source: [4].

2. 3 The algorithm of hybridized neutrosophic 2-tuple Linguistic model and ARAS Model

In this subsection, we recall the characteristics of the model that combines the neutrosophic linguistic 2-tuple model with the ARAS multi-criteria decision-making model [4]. See other approaches to Neutrosophic ARAS in [17, 18]. We explain this in the following steps:

1. Let us start from a set $E = \{e_1, e_2, \dots, e_k\}$ of $k \geq 1$experts, and $C = \{c_1, c_2, \dots, c_n\}$ are n criteria to measure m feasible alternatives $A = \{a_1, a_2, \dots, a_m\}$, as in the original ARAS method.

For each criterion, there is a linguistic measurement scale consisting of a set $S_i = \{s_1^i, s_2^i, \dots, s_{l_i}^i\}$ where l_i is an odd number.

2. Each expert e_p evaluates each alternative a_j according to the criterion c_i, giving a triad $\left(s_{jpq_T}^i, s_{jpq_I}^i, s_{jpq_F}^i\right)$ where $s_{jpq_T}^i \in S_i$ means the linguistic evaluation given by the expert p that the alternative meets the given criterion. See that q_T is the index of the linguistic term within the set S_i. Similarly, $s_{jpq_I}^i$ indicates the linguistic label for indeterminacy and $s_{jpq_F}^i$ for falsehood.

   This includes the evaluation of an ideal alternative a_0 for each of the criteria. The evaluations of this ideal alternative are obtained from experts either as the maximum of the values obtained when the maximum is preferable, or the minimum when this is preferable.

3. The triads $\left(s_{jpq_T}^i, s_{jpq_I}^i, s_{jpq_F}^i\right)$ are aggregated for each criterion and each alternative for all experts. To do this, the arithmetic mean is used concerning all the experts of the given evaluations. In this way, the following values are obtained:

   $\left(\bar{s}_{jq_T}^i, \bar{s}_{jq_I}^i, \bar{s}_{jq_F}^i\right)$ with $\beta_T = \frac{\sum_{p=1}^k q_T}{k}$, $\beta_I = \frac{\sum_{p=1}^k q_I}{k}$, and $\beta_F = \frac{\sum_{p=1}^k q_F}{k}$ (14)

   To simplify the notations, there are $r_j^i = \left({\beta_T}_j^i, {\beta_I}_j^i, {\beta_F}_j^i\right) \in [0, l_i]^3$ where beta values are obtained for each of the evaluations for truthfulness, falsity, and indeterminacy, respectively.

   This is how the matrix that appears in Equation 15 is formed.

$$X_\beta = \begin{bmatrix} r_0^1 & \cdots & r_o^j & \cdots & r_0^n \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_i^1 & \cdots & r_i^j & \cdots & r_i^n \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_m^1 & \cdots & r_m^j & \cdots & r_m^n \end{bmatrix} i = 1,2, \dots, m; j = 1,2, \dots, n \quad (15)$$

4. Now the values of the matrix X_β are normalized as follows:

   The criteria whose ideal values are maximum are normalized with Equation 16.

$$\bar{r}_i^j = \frac{r_i^j}{\sum_{i=0}^m r_i^j} \quad (16)$$

Thus, $\bar{r}_j^i = \left(\frac{\beta_{T_j}^i}{\sum_{t=0}^m \beta_{T_j}^t}, \frac{\beta_{I_j}^i}{\sum_{t=0}^m \beta_{I_j}^t}, \frac{\beta_{F_j}^i}{\sum_{t=0}^m \beta_{F_j}^t}\right)$.

The criteria whose values are minimum are normalized with the following Equations:

$$r_i^j = \frac{1}{r_i^{j*}}, \bar{r}_i^j = \frac{r_i^j}{\sum_{i=0}^m r_i^j} \quad (17)$$

5. Then, we have the values $\bar{r}_i^j = (\gamma_T, \gamma_I, \gamma_F) \in [0,1]^3$. To convert them to a scalar value in $[0,1]$, formula 18 is used.
$$\lambda(\bar{r}_i^j) = \frac{2+\gamma_T-\gamma_I-\gamma_F}{3} \quad (18)$$
Let us call it $\bar{x}_{ij} = \lambda(\bar{r}_i^j)$.
6. The original ARAS method is applied to the above results, applying Equations 7-13 to the values $\bar{x}_{ij}$.

Figure 2 contains a schematic of the proposed algorithm.

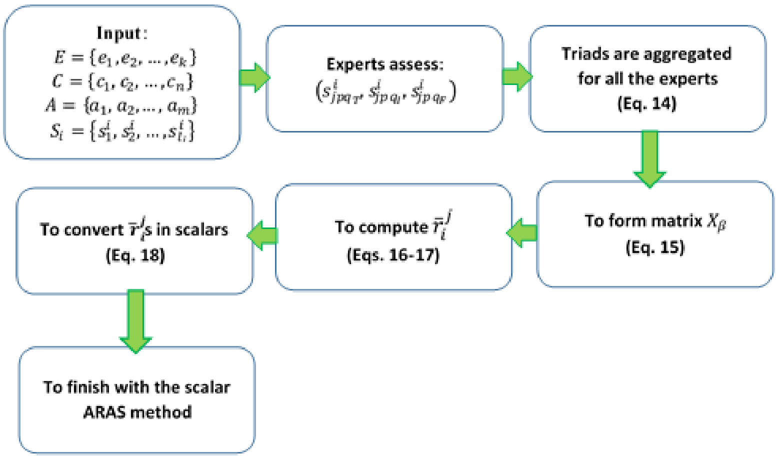

Figure 2: Scheme of the ARAS algorithm hybridized with the neutrosophic 2-tuple linguistic model for multi-criteria decision-making. Source [4].

3 Analyzing the AI Literacy Program

3.1 Keynotes on DigCompEdu

The European Framework for the Digital Competence of Educators (DigCompEdu) is a scientifically solid framework, which describes the meaning of digitally competent educators. DigCompEdu identifies the digital competencies necessary to perform the teaching role effectively. The framework is designed to be used by professionals at all educational levels, from early childhood education to higher education, as well as by educators working with students with special needs or in non-formal learning contexts.

DigCompEdu is composed of six areas of competence:

- Competency 1: To understand the basic concepts of digital technology;
- Competency 2: To use digital technologies for learning and teaching;
- Competency 3: To create digital content;
- Competency 4: To evaluate the use of digital technologies;
- Competency 5: To participate in the digital society;
- Competency 6: To guide students in the use of digital technologies.

Additionally, the framework also provides a progression of competencies, allowing educators to evaluate their progress over time (Figure 3).

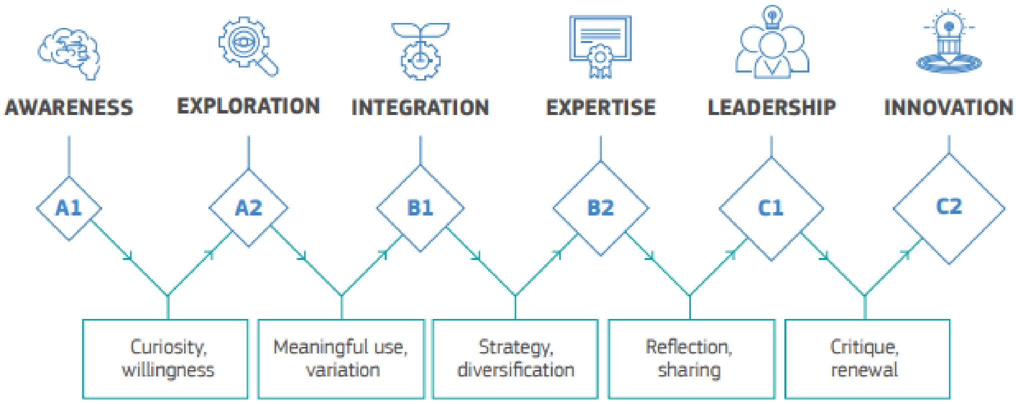

Figure 3 . DigiCompEdu Progression Model.

Although DigCompEdu is a robust framework, it could be updated by adding a new competence area on AI literacy. This competence area would cover topics such as the basic concepts of AI, its applications in education, and its ethical implications; and the review of existing competence areas to reflect the role of AI in education such as the "Use digital technologies for learning and teaching". Given the interest, development, and widespread use of DigComp in general and DigCompEdu in particular, we understand that it is a proposal that can be valid as a guide to propose a teacher training program in the short and medium term.

Concerning the integration of Generative AI in the Latin American educational context, we have to highlight the importance of developing digital teaching competencies within a framework adapted to the cultural, disciplinary, and technological access particularities of the region. Questioning the direct applicability of the European DigCompEdu framework, an adaptation is advocated, which respects diversity and guarantees equitable and culturally relevant digital training for teachers, see Figure 4. This perspective emphasizes the need to consider the different realities of educational communities and, if necessary, promote the creation and customization of frameworks that maximize local strengths and opportunities.

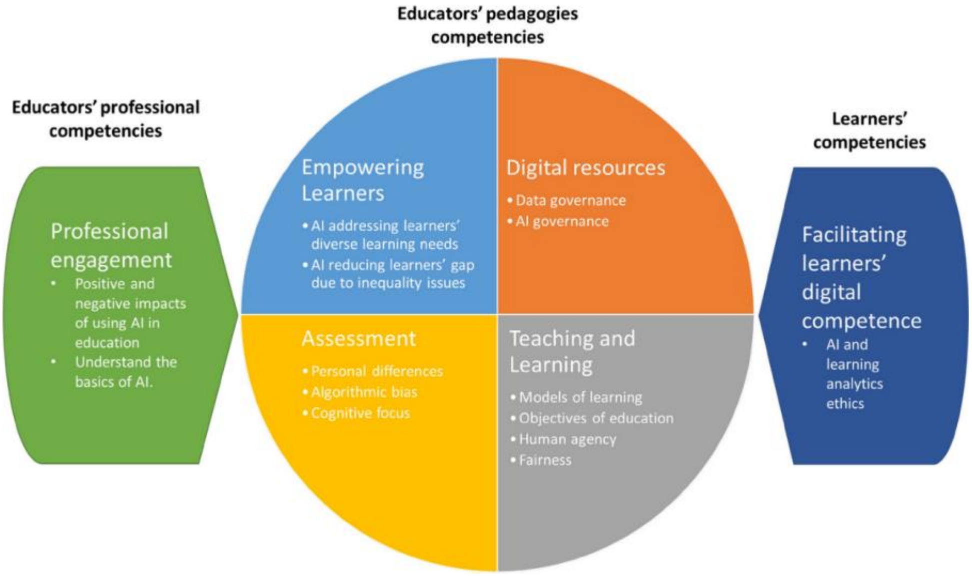

Figure 4. DigCompEdu framework for teachers' AI competence.

On the other hand, the importance of comprehensive professional development for teachers is highlighted, which not only covers knowledge of AI but also a deep understanding of its ethical implications and limitations. Likewise, the importance of staying up to date on emerging technologies such as the Metaverse, blockchain, and cloud computing is highlighted, as disruptive technologies that students will face in their professional future, for which we must prepare them, but first, they must be trained in this sense.

In this context, a training program is proposed that is distinguished by its flexibility and adaptability, which allows its effective implementation in various educational contexts, whether in institutions of the same level or at different educational levels. Its modular design must cover everything from the fundamentals to the specific application of artificial intelligence in education, allowing it to be adjusted according to the particular needs of each institution. This feature not only ensures that the program is relevant to different academic realities, but also facilitates the incorporation of context-specific pedagogical approaches.

The scalability of the program is supported by its well-defined structure and the inclusion of periodic evaluations, which allow measuring participants' progress. The results obtained from these evaluations will serve to provide feedback to adapt the program in real-time and provide valuable data for future implementations in other educational institutions.

The institution Bolivarian University of Ecuador is distinguished by its youth and determined commitment to entering into scientific research. In line with an innovative vision, the Bolivarian University of Ecuador recognizes the urgent need to prepare its teachers and students to address emerging challenges in technological development, especially AI. As an incipient and dynamic educational entity, this academic institution is in a crucial stage of its evolution, seeking not only to consolidate its presence in the academic field but also to place its professionals at the forefront of educational and technological transformations.

Based on the analyses carried out on the AI competence frameworks, aimed at teachers, the following training program is proposed:

General goal: To develop the necessary skills for teachers to use Artificial Intelligence effectively and ethically in the teaching and learning process.

Program Duration: The training program can be carried out over 3 months, with regular training sessions and practical activities.

Module 1: AI Fundamentals:

- History and evolution of Artificial Intelligence.
- Basic concepts. Types of AI and their applications in various sectors
- Fundamental principles of operation of AI.
- Ethics and responsibility in the development of AI.

Module 2: Application of AI in Education:

- Personalization of learning: Strategies and tools.
- Intelligent feedback and adaptive assessment.
- Integration of AI in curricular planning.
- Educational gamification that is supported by AI.
- Impact of AI on educational equity and diversity.

Module 3: Ethics and Critical Thinking about AI:

- Ethical and social implications of AI in the educational field.
- Reflection on equity and diversity in the use of AI.
- Ethical decision-making in educational situations with AI.
- Individual and collective responsibility in the use of AI.

Module 4: Integration of AI in Pedagogy:

- Design of innovative educational activities with AI.
- Effective AI-assisted teaching strategies.
- Evaluation of the impact of AI on the learning process.
- Development of educational content with a focus on AI.

Module 5: Application of AI in Research (Optional: Aimed at University Professors):

- Use of AI in research data collection and analysis.
- Advanced AI tools and techniques for research.
- Innovations and advances in research facilitated by AI.
- Integration of AI in the publication and dissemination of results.
- Ethics in research supported by AI.

Training methodology:

The training program will adopt a holistic approach, combining theoretical sessions, workshops, practical activities, group discussions, and case studies. The active participation of teachers will be encouraged by promoting collaboration and the exchange of experiences. Additional resources, such as supplemental readings and access to educational AI platforms, will be provided to enrich learning.

Evaluation and monitoring:

Periodic evaluations will be carried out to measure teachers' progress in developing AI competencies. Additionally, individualized feedback and follow-up sessions will be conducted to address the specific needs of participants. To this end, as the next phase of research, a test is being developed to measure AI literacy based on the analyzed frameworks, which can help diagnosing the current and desired state considering the development of teachers' AI competencies.

The AI literacy framework is presented as a comprehensive and well-structured tool for the development of artificial intelligence competencies among educators. It consists of seven key areas ranging from the fundamentals of AI to preparing educators for the future of work. The clear progression and three levels of mastery provide a gradual and adaptive approach for educators who want to improve their AI skills. Its holistic approach and clear structure position it as a guide to consider for continuous professional development in an educational context transformed by AI. The framework consists of seven key areas:

1. AI Fundamentals: It covers the basics of AI, such as the history of AI, different types of AI, and the working principles of AI.
2. Data flow: It focuses on the use of data to train and improve AI systems. Educators at this level must demonstrate a basic understanding of data collection, preparation, and analysis techniques. They must also be able to identify and interpret data patterns relevant to AI applications in education.
3. Critical Thinking and Fact Checking: It explores how educators can critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace. They must be able to assess the credibility and reliability of information generated by AI, identify potential biases and limitations, and use AI ethically and responsibly.
4. Diverse AI use cases: It examines how AI is used in different fields, such as education, medicine, and business. Educators must be able to understand the potential benefits and challenges of AI in various contexts and identify suitable applications for AI in their teaching practice.
5. Ethics of AI: It recognizes the ethical and social implications of using AI. Educators should be aware of potential ethical issues surrounding AI, such as bias, discrimination, and privacy, and be able to make informed decisions about integrating AI into their classrooms.
6. AI Pedagogy: It focuses on educators' ability to use AI to improve teaching and learning. They must be able to identify and select appropriate AI tools and resources that suit their teaching objectives and the needs of their students. They must also be able to seamlessly integrate AI into their lessons and adapt their pedagogy to accommodate AI-enhanced learning experiences.
7. Future of Work: It explores how AI is transforming the world of work and how educators can prepare students for future success. They must understand the impact of AI on various professions and be able to guide students in developing the skills and competencies necessary to thrive in an AI-driven workforce.

The framework also defines three levels of mastery:

1. Introductory: Students at this level develop a basic understanding of the topic. They can identify and describe key concepts but may lack in-depth knowledge or practical application of the subject.
2. Intermediate: At this level, learners demonstrate a deeper understanding of the topic. They can analyze, evaluate, and synthesize information, and can apply their knowledge to solve problems or make informed decisions.
3. Advanced: Lastly, they do not only deeply understand the topic, but they also contribute to it. They can create and curate content, provide intellectual leadership, and engage in strategic activities within the field. They can also actively participate in the community, consult with others, and share their experience.

So, these preceding aspects serve as the attributes and scale to assess the proposed program. See the next subsection.

3.2 Proposed assessment at Bolivarian University of Ecuador (BUE)

To evaluate the relevance of the program, five academics from the BUE were involved, who are acknowledged pedagogical authorities and knowledgeable about AI applied to teaching. As previously specified, the five experts must evaluate three alternatives (A1) Teaching classes 80% theoretical 20% practical (A2) Teaching classes 50% theoretical and 50% practical (A3) Teaching classes 20% theoretical 80% practical.

The evaluation criteria were specified previously, they are based on evaluating how the alternative allows achievements in the following aspects:

C1: AI Fundamentals.
C2: Data flow.
C3: Critical Thinking and Fact-Checking.
C4: Diverse AI use cases.

C5: Ethics of AI.
C6: AI Pedagogy.
C7: Future of Work.
The evaluation scale contains three elements:
$S = \{s_1, s_2, s_3\}$ where they mean the following:
s_1: By applying this alternative in the measured aspect, the teacher will reach an "Introductory" level in the short or medium term.
s_2: By applying this alternative in the measured aspect, the teacher will reach an "Intermediate" level in the short or medium term.
s_3: By applying this alternative in the measured aspect, the teacher will reach an "Advanced" level in the short or medium term.
a_0 was defined with the following values (s_3, s_3, s_1) for all the criteria, where the first two terms are equal because it means that there is no indeterminacy.

The five specialists issued their opinions after carefully studying the program, consulting the designers if necessary, and analyzing possible variants of class delivery.

The results of the experts' evaluation of each of the attributes and alternatives are summarized below.

Criterion/Alternative	a_0 = Optimal	A1	A2	A3
C_1	(3,3,1)	(3,3,1)	(3,2,1)	(2,2,1)
C_2	(3,3,1)	(2,2,1)	(3,2,1)	(3,3,1)
C_3	(3,3,1)	(3,3,1)	(3,2,1)	(2,2,1)
C_4	(3,3,1)	(3,3,1)	(3,2,1)	(2,2,1)
C_5	(3,3,1)	(3,3,1)	(3,2,1)	(2,2,1)
C_6	(3,3,1)	(2,2,1)	(3,3,1)	(2,2,1)
C_7	(3,3,1)	(2,2,1)	(3,3,1)	(3,2,1)

Table 1: Matrix of evaluations with the triple betas added for all experts for each alternative.

In Table 1 the triads appear in the form of evaluation indices, where each index is the result of calculating the median and not the arithmetic means of the evaluations given by the experts, which are the beta values. Note that the tables are represented with the transposed matrices.

Table 2 summarizes the normalized triads.

Criterion/Alternative	a_0 = Optimal	A1	A2	A3
C_1	(0.27,0,0.25)	(0.27,0,0.25)	(0.27,0.25,0.25)	(0.18,0,0.25)
C_2	(0.27,0,0.25)	(0.18,0,0.25)	(0.27,0.25,0.25)	(0.27,0,0.25)
C_3	(0.27,0,0.25)	(0.27,0,0.25)	(0.27,0.25,0.25)	(0.18,0,0.25)
C_4	(0.27,0,0.25)	(0.27,0,0.25)	(0.27,0.25,0.25)	(0.18,0,0.25)
C_5	(0.27,0,0.25)	(0.27,0,0.25)	(0.27,0.25,0.25)	(0.18,0,0.25)
C_6	(0.3,0,0.25)	(0.2,0,0.25)	(0.3,0,0.25)	(0.2,0,0.25)
C_7	(0.27,0,0.25)	(0.18,0,0.25)	(0.27,0,0.25)	(0.27,0.25,0.25)

Table 2: Matrix of evaluations with the triple betas from Table 1 normalized.

Note that in Table 2 in the indeterminacy component, the formula $abs(t - i)$ was used and then normalized. Next, Equation 18 is applied in Table 3.

Criterion/Alternative	a_0 = Optimal	A1	A2	A3
C_1	0.67333	0.67333	0.59	0.64333
C_2	0.67333	0.64333	0.59	0.67333
C_3	0.67333	0.67333	0.59	0.64333
C_4	0.67333	0.67333	0.59	0.64333
C_5	0.67333	0.67333	0.59	0.64333
C_6	0.68333	0.65	0.68333	0.65

C_7	0.67333	0.64333	0.67333	0.59

Table 3: Matrix of evaluations with the results of Table 2 converted into numerical values.

The data obtained from Table 3 are normalized according to Equation 7.

Criterion/Alternative	a_0 = Optimal	A1	A2	A3
C_1	0.260981632	0.26098163	0.22868306	0.24935368
C_2	0.260981632	0.24935368	0.22868306	0.26098163
C_3	0.260981632	0.26098163	0.22868306	0.24935368
C_4	0.260981632	0.26098163	0.22868306	0.24935368
C_5	0.260981632	0.26098163	0.22868306	0.24935368
C_6	0.256249391	0.24375061	0.25624939	0.24375061
C_7	0.260981632	0.24935368	0.26098163	0.22868306

Table 4: Matrix of the normalized elements of Table 3.

The summary of the results of the classic ARAS applied to the data in Table 4 can be observed in Table 5 with the weights $w_j = \frac{1}{7}$.

Alternative	a_0 = Optimal	A1	A2	A3
Optimality	0.260305597	0.25519779	0.23723519	0.24726143
Utility	1	0.98037763	0.91137182	0.94988903
Ranking	-	1	3	2

Table 5: Optimality and utility values of the ARAS crisp method for the results of Table 4.

According to the results of Table 5 and the experts' criteria, it is preferred to apply a pedagogical strategy with a proportion of 80% theoretical and 20% practical.

Conclusion

Artificial Intelligence is one of the scientific disciplines that is currently causing the greatest social impact in today's world. Its correct application depends on access to technological means, but also on the preparation of citizens for their correct use, including ethics. Its teaching is essential at all school levels so that students are then able to incorporate it into their daily lives and also professional. The purpose of this paper was to determine the pedagogical strategy to follow for a program where DigiComEdu is adapted from the European level to the conditions of a Latin American country, specifically at the Bolivarian University of Ecuador. A group of experts was consulted to evaluate three strategies: (1) Teaching classes 80% theoretical 20% practical (2) Teaching classes 50% theoretical and 50% practical (3) Teaching classes 20% theoretical 80% practical. The criteria to be evaluated were seven. A linguistic scale was used to carry out the evaluations and a hybrid method of neutrosophic linguistic 2-tuple model and the ARAS method was applied for decision making. It was concluded that the best strategy is teaching 80% theoretical classes and 20% practical classes.

GRATITUDE:

To the Universidad Bolivariana del Ecuador for the support and financing for the development of the Research Project "Right to education in new technologies" making this possible to achieve the established objective.

References

[1] Castelvecchi, D. (2016). Can we open the black box of AI? Nature, 538, 20-23.

[2] Flores-Ledesma, K.N., Navas Rios, M.E., Venturo Orbegoso, C.O., Lora Loza, M.G, Gómez-Zuluaga, C.M., Meneses-La Riva, M.E.; Vallina-Hernández, A.M., and Flores-Sotelo, W.S. (2024). A hybrid of ARAS and neutrosophic 2-tuple linguistic model to evaluate gender equitable policies from the perspective of Latin American professors. Neutrosophic Sets and Systems, 62, 20-27.
[3] Fan, J., Yan, F., and Wu, M. (2021). GLDS method for multiple attribute group decision making under 2-Tuple linguistic neutrosophic environment. Journal of Intelligent & Fuzzy Systems, 40, 11523-11538.
[4] Liu, N., and Xu, Z. (2021). An overview of ARAS method: Theory development, application extension, and future challenge. International Journal of Intelligent Systems, 36, 3524-3565.
[5] AL-Baker S.F., Elhenawy, I., and Mohamed, M. (2024) Exploring the Influences of Metaverse on Education Based on the Neutrosophic Appraiser Model. International Journal of Neutrosophic Science, 23, 134-145.
[6] Moussa, N., Bentoumi, R., Saali, T. (2024) Promoting Student Success with Neutrosophic Sets: Artificial Intelligence and Student Engagement in Higher Education Context. International Journal of Neutrosophic Science, 23, 238-248.
[7] Alnaqbi, N.M., and Fouda, W. (2023) Exploring the Role of ChatGPT and social media in Enhancing Student Evaluation of Teaching Styles in Higher Education Using Neutrosophic Sets. International Journal of Neutrosophic Science, 20, 181-190.
[8] Smarandache, F., and Leyva-Vazquez, M. (2018). Fundamentals of neutrosophic logic and sets and their role in artificial intelligence (Fundamentos de la lógica y los conjuntos neutrosóficos y su papel en la inteligencia artificial). Neutrosophic Computing and Machine Learning, 1, 3-8.
[9] M.Ali, A. and Muthuswamy, M. (2023) "Neutrosophic Multi-Criteria Decision-Making Framework for Sustainable Evaluation of Power Production Systems in Renewable Energy Sources", Sustainable Machine Intelligence Journal, 4, pp. (3):1–10. doi:10.61185/SMIJ.2023.44103.
[10] Christianto, V., and Smarandache, F. (2020). Remark on Artificial Intelligence, humanoid and Terminator scenario: A Neutrosophic way to futurology. Infinite Study.
[11] El-Douh, A. (2023) "A Neutrosophic Multi-Criteria Model for Evaluating Sustainable Soil Enhancement Methods and their Cost Implications in Construction", Sustainable Machine Intelligence Journal, 5, pp. (1):1–11. doi:10.61185/SMIJ.2023.55101.
[12] Şahin, S., Kargın, A., and Yücel, M. (2021). Hausdorff Measures on Generalized Set Valued Neutrosophic Quadruple Numbers and Decision-Making Applications for Adequacy of Online Education. Neutrosophic Sets and Systems, 40, 86-116
[13] Cruz, M. F., Vargas, M. E. R., Cadena, K. A. Á., Carolina, D., and Delgado, O. (2021). Studying health and inclusive education: sentiment analysis using neutrosophy as a research tool. Neutrosophic Sets and Systems, 42, 324-332.
[14] Wang, J., Wei, G., and Wei, Y. (2018). Models for green supplier selection with some 2-tuple linguistic neutrosophic number Bonferroni mean operators. Symmetry, 10, 131.
[15] Chen, H. (2023). A multi-attribute decision-making framework for enterprise competitive intelligence system evaluation with 2-tuple linguistic neutrosophic information. Journal of Intelligent & Fuzzy Systems, (Preprint), 1-16.
[16] Wei, G., Wu, J., Guo, Y., Wang, J., and Wei, C. (2021). An extended COPRAS model for multiple attribute group decision making based on single-valued neutrosophic 2-tuple linguistic environment. Technological and Economic Development of Economy, 27, 353-368.
[17] Adalı, E. A., Öztaş, T., Özçil, A., Öztaş, G. Z., and Tuş, A. (2023). A new multi-criteria decision-making method under neutrosophic environment: ARAS method with single-valued neutrosophic numbers. International Journal of Information Technology & Decision Making, 22(01), 57-87.
[18] .Simic, V., Dabic-Miletic, S., Tirkolaee, E. B., Stević, Ž., Ala, A., and Amirteimoori, A. (2023). Neutrosophic LOPCOW-ARAS model for prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems. Applied Soft Computing, 143, 110400.
[19] Nabeeh, N. (2023) "Assessment and Contrast the Sustainable Growth of Various Road Transport Systems using Intelligent Neutrosophic Multi-Criteria Decision-Making Model", Sustainable Machine Intelligence Journal, 2, pp. (2):1–12. doi:10.61185/SMIJ.2023.22102.

Received: March 5, 2024. Accepted: July 30, 2024