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Strategies for socio-emotional well-being in medical training with artificial intelligence using neutrosophic AHP.

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Abstract

This article analyzes the socio-emotional impact of artificial intelligence (AI) on the teaching-learning process of medical science students, using the Neutrosophic Analytic Hierarchy Process (NAHP) to prioritize educational strategies that promote emotional well-being and comprehensive professional development. Through a systematic review based on PRISMA and primary data collected through surveys, key socio-emotional factors, such as anxiety, empathy, and resilience, were identified as affected by the use of AI. The NAHP modeled uncertainty in students' and teachers' perceptions through neutrosophic values, structuring criteria (stress reduction, empathy promotion, and communication improvement) and alternatives (human mentoring, teacher training, AI-enhanced simulators). The results highlight priority strategies for integrating AI ethically, minimizing negative emotional impacts and strengthening interpersonal skills. This approach contributes to the design of medical curricula that balance technical and socio-emotional competencies, preparing future professionals for compassionate and effective medical practice in a technologically advanced context.

Keywords: Artificial Intelligence, Medical Education, Socio-emotional Aspects, Neutrosophic Hierarchical Analytic Process.

1. Introduction

The integration of artificial intelligence (AI) in medical education has emerged as a transformative pillar of the teaching-learning process, but it poses significant socio-emotional challenges that affect both students and faculty. This study analyzes the socio-emotional impacts of AI on medical

science students, employing the Neutrosophic Analytic Hierarchy Process (NAHP) to prioritize educational strategies that promote emotional well-being and comprehensive professional development. The relevance of this research lies in the need to train physicians not only to be technically competent, but also to develop essential interpersonal skills, such as empathy and resilience, in a context where technology is redefining medical practice [1]. Recent studies highlight that AI improves diagnostic accuracy, but can generate anxiety or reduce human connection in medical training [2], [3]. This work addresses this gap, proposing a structured approach to balance technological benefits with socio-emotional development.

Historically, medical education has evolved from traditional memorization-focused methods to competency-based approaches, integrating technologies such as simulators and machine learning systems [4]. Over the past two decades, AI adoption has grown exponentially, with tools such as virtual tutors and diagnostic support systems transforming teaching [5]. However, this technological transition has brought with it emotional challenges, such as stress due to dependence on AI or the perception of dehumanization in patient interactions [6]. In global contexts, from North America to Asia, the literature reports growing concern about how AI affects empathy and teamwork, critical skills for medical practice [7].

The central problem of this research arises from the lack of systematic approaches that assess and mitigate the socio-emotional impacts of AI in medical training. Although the literature recognizes the potential of AI to improve learning, a gap persists in understanding how these technologies influence anxiety, empathy, or resilience in students and teachers [8]. The question that guides this study is: how can educational strategies be designed that, considering the uncertainty of socio-emotional perceptions, optimize well-being and interpersonal skills in medical students using AI? This question underscores the need for an analysis that integrates emotional complexity with technological innovation. Despite advances in the integration of AI, few studies have explored its impact from a socio-emotional perspective, especially in the medical context, where empathy and communication are fundamental [9]. The uncertainty inherent in human perceptions—such as enthusiasm or apprehension about AI—requires methods capable of handling ambiguity, such as the NAHP, which incorporates neutrosophic values to model truth, falsity, and indeterminacy. This approach allows for prioritizing educational strategies that consider the subjectivity of emotions, a critical aspect in the training of healthcare professionals. The relevance of this study is reinforced by the growing reliance on AI in clinical settings, which requires preparing future physicians to navigate these challenges with emotional and technical intelligence.

The NAHP is selected as a methodological tool for its ability to structure complex decisions in uncertain environments, a common scenario when assessing human emotions. Unlike traditional methods, the NAHP allows weighting to be assigned to criteria such as stress reduction or empathy promotion, considering the uncertainty in the responses of students and teachers. This study is based on a systematic literature review and primary data collected through surveys, ensuring a rigorous and grounded approach. The results seek to inform the design of medical curricula that balance technological innovation and human development. The magnitude of the problem is evident in the literature, which reports an increase in anxiety among medical students exposed to AI tools, particularly in high-pressure specialties such as surgery or diagnostic imaging [3]. This anxiety can affect not only academic performance but also the ability of future physicians to connect with patients empathically. Furthermore, educators face their own emotional challenges, such as uncertainty regarding the integration of AI into their teaching methods [6]. The lack of clear strategies to address these socioemotional impacts could compromise the quality of medical training and, ultimately, patient care.

This study aims to fill this gap by offering an innovative perspective on how AI can be integrated into medical education without sacrificing the human component. By employing the NAHP, it seeks not only to identify key socioemotional factors but also to prioritize practical interventions that promote well-being and resilience. The research aligns with the global need to train physicians who combine technical competencies with emotional intelligence, an essential balance in modern medicine [7]. The findings will have implications for educational program design and institutional policies in medical universities.

The objectives of this study are twofold. First, to analyze the socioemotional aspects that influence the teaching-learning process with AI in medical science students, identifying factors such as anxiety, empathy, and interpersonal communication. Second, to prioritize, through the NAHP, educational strategies that optimize the educational experience and promote comprehensive professional development, ensuring that future physicians are prepared for ethical and compassionate practice in a technologically advanced context. These objectives guide the research toward a practical and theoretically grounded solution, answering the research question and contributing to the advancement of medical education.

2. Materials and methods

2.1. **Analysis and Assessment of Socio-Emotional Well-being in Medical Training.**

Socio-emotional well-being, understood as the balance between emotions, empathy, and interpersonal skills, constitutes an essential pillar in the training of medical professionals, particularly in a context where artificial intelligence (AI) transforms the teaching-learning process. The integration of tools such as virtual simulators or AI-based diagnostic systems has revolutionized medical education, improving technical accuracy, but also generates significant emotional challenges, such as anxiety or decreased empathy towards patients [10]. This analysis evaluates how the Neutrosophic Analytic Hierarchy Process (NAHP) can prioritize educational strategies that optimize socio-emotional well-being, addressing the uncertainty inherent in human perceptions. The relevance of this approach lies in its ability to structure complex decisions, considering not only the technical benefits of AI, but also its impact on resilience and human connection.

Medical education has transitioned from traditional approaches to advanced technological models, where AI plays a central role. However, this technological evolution is not always accompanied by an in-depth analysis of its emotional effects. Recent studies indicate that medical students experience anxiety when relying on AI tools for diagnoses, fearing a potential disconnect with patients [11]. On the other hand, educators face uncertainty when integrating these technologies into their teaching methods, which can generate apprehension or resistance [12]. The NAHP, by incorporating neutrosophic values (truth, indeterminacy, falsity), offers a robust tool for modeling these ambiguous perceptions, allowing for the identification of strategies that balance innovation and emotional well-being.

Socioemotional well-being is not limited to the absence of stress, but encompasses students' ability to develop empathy, effective communication, and resilience in the face of technological challenges . AI, although efficient, can reduce opportunities for human interaction, a critical component of medical training [10]. For example, prolonged use of virtual simulators can improve technical skills but also generate a perception of dehumanization in clinical practice. The NAHP addresses this issue by structuring criteria such as anxiety reduction, fostering empathy, and improving interpersonal skills, assigning them weights that reflect the uncertainty of students' and faculty members' perceptions. This approach ensures that prioritized educational strategies are holistic and focused on human development.

One argument in favor of NAHP is its ability to handle the inherent subjectivity of human emotions, an aspect that traditional methods, such as classical AHP, fail to accurately capture. By employing neutrosophic values, NAHP allows for the modeling of contradictory responses, such as enthusiasm for AI's accuracy combined with fear of losing interpersonal skills [12]. For example, a student might value AI for its efficiency, but feel uncertain about its impact on empathy towards patients. This method, by integrating indeterminacy, offers a more complete view of socio-emotional dynamics, making it ideal for medical contexts where emotions are complex and multifaceted.

However, the implementation of the NAHP is not without challenges. Primary data collection, through surveys or interviews, can be limited by subjective biases or the difficulty of quantifying emotions such as empathy. Furthermore, the application of neutrosophic values requires a level of mathematical expertise that may not be available in all academic settings. However, these limitations are mitigated by combining the NAHP with a systematic literature review, using databases such as PubMed or Scopus, which bases decisions on solid scientific evidence [11]. This mixed approach ensures that the identified strategies are both theoretically robust and practically applicable.

The assessment of socioemotional well-being in this context transcends the individual sphere, impacting the quality of future medical care. Literature suggests that physicians with high emotional intelligence provide more empathetic and effective care, which improves clinical outcomes [11]. By prioritizing educational strategies that reinforce resilience and communication, the NAHP contributes to training professionals capable of integrating AI without compromising their humanity. For example, strategies such as teacher training in emotional intelligence or the design of simulators that simulate human interactions can mitigate the negative effects of AI, promoting a balance between technical competence and emotional connection.

Another aspect to consider is the adaptability of the NAHP to different medical specialties. The literature indicates that the socioemotional impact of AI varies according to the training area; for example, surgical students report greater anxiety regarding AI than those in general medicine [12]. The NAHP allows educational strategies to be customized according to these contexts, assigning specific weights to criteria relevant to each specialty. This flexibility ensures that interventions are relevant and effective, addressing the specific needs of each group of students and faculty.

The case for the NAHP also rests on its potential to inform institutional-level educational policies. Medical universities face the challenge of integrating AI without neglecting socioemotional development, a balance that requires evidence-based decisions. By providing a ranking of educational strategies, the NAHP offers institutions a practical tool for designing curricula that promote well-being. For example, prioritizing human mentoring alongside AI could reduce anxiety and foster empathy, strengthening future physicians' preparation for ethical practice.

Critically, this approach not only benefits students but also empowers faculty, who play a key role in shaping attitudes toward AI. Faculty training in the emotional management of technology can mitigate their own uncertainty, allowing them to guide students more effectively. However, successful implementation of the NAHP requires an institutional commitment to collecting quality data and training staff in its use. Despite these demands, the benefits of a structured, evidence-based approach outweigh the costs, especially in a context where AI is redefining medical education.

In conclusion, socioemotional well-being is a critical component of medical education, and NAHP offers an innovative solution to address the challenges posed by AI. By modeling the uncertainty of human perceptions and prioritizing educational strategies, this method promotes a balance between technological innovation and human development. The results of this approach not only optimize the educational experience but also prepare future physicians for compassionate and effective

practice. The adoption of NAHP in medical education represents a step toward more holistic training, ensuring that technology serves as an ally, not a hindrance, in the development of healthcare professionals.

2.2. Neutrosophic Set.

Neutrosophic set theory is a novel approach that challenges traditional binary logic by introducing a third component: indeterminacy. This trichotomous model—which includes truth, falsity, and indeterminacy—is designed to reflect the ambiguity present in real-world phenomena and human decisions where certainty is often elusive. Unlike fuzzy sets, which use degrees of membership, this theory captures the essence of vagueness in subjective judgments or contradictory data. Its ability to model ambiguity makes it a valuable tool for applications in fields like artificial intelligence and medicine, where it can help manage incomplete or conflicting information and improve decision support systems. While some critics argue that the indeterminate state adds unnecessary complexity, this perspective overlooks the theory's power in analyzing situations where uncertainty is unavoidable and where traditional methods fall short. Overall, neutrosophic sets represent a significant step in formalizing uncertainty and provide a more flexible and accurate framework for understanding the complexities of the modern world.

Definition 1 ([13-15]) : The *neutrosophic set N* It is characterized by three membership functions, which are the truth membership function T_A, the indeterminacy membership functionI_A and falsehood membership function F_A , where U is the Universe of Discourse and $\forall x \in U$, $T_A(x), I_A(x), F_A(x) \subseteq]^{-}0, 1^{+}[$, and $^{-}0 \leq \inf T_A(x) + \inf I_A(x) + \inf F_A(x) \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^{+}$.

See that, by definition, $T_A(x), I_A(x)$and $F_A(x)$are standard or nonstandard real subsets of $]^{-}0, 1^{+}[$and, therefore, $T_A(x), I_A(x)$and $F_A(x)$can be subintervals of $[0, 1]$. $^{-}0$and1^{+} They belong to the set of hyperreal numbers.

Definition 2 ([13-15] : The *single- valued neutrosophic set (* SVN S) $A$is U, $T_A: U \rightarrow [0, 1]$where $A = \{< x, T_A(x), I_A(x), F_A(x) > : x \in U\}$and $I_A: U \rightarrow [0, 1]$. $F_A: U \rightarrow [0, 1]$.$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$

The single-valued neutrosophic number (SVN) N) is symbolized by

$N = (t, i, f)$, such that$0 \leq t, i, f \leq 1$ and $0 \leq t + i + f \leq 3$.

Definition 3 ([13-15]) : The *single -valued triangular neutrosophic number* , $\tilde{a} = \langle (a_1, a_2. a_3); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle$, is a neutrosophic set in $\mathbb{R}$, whose truth, indeterminacy and falsity membership functions are defined as follows:

$$T_{\tilde{a}}(x) = \begin{cases} \alpha_{\tilde{a}}\left(\frac{x-a_1}{a_2-a_1}\right), a_1 \leq x \leq a_2 \\ \alpha_{\tilde{a}}, x = a_2 \\ \alpha_{\tilde{a}}\left(\frac{a_3-x}{a_3-a_2}\right), a_2 < x \leq a_3 \\ 0, \text{otherwise} \end{cases} \quad (1)$$

$$I_{\tilde{a}}(x) = \begin{cases} \frac{(a_2-x+\beta_{\tilde{a}}(x-a_1))}{a_2-a_1}, a_1 \leq x \leq a_2 \\ \beta_{\tilde{a}}, x = a_2 \\ \frac{(x-a_2+\beta_{\tilde{a}}(a_3-x))}{a_3-a_2}, a_2 < x \leq a_3 \\ 1, \text{otherwise} \end{cases} \quad (2)$$

$$F_{\tilde{a}}(x) = \begin{cases} \frac{(a_2 - x + \gamma_{\tilde{a}}(x - a_1))}{a_2 - a_1}, a_1 \le x \le a_2 \\ \gamma_{\tilde{a}}, x = a_2 \\ \frac{(x - a_2 + \gamma_{\tilde{a}}(a_3 - x))}{a_3 - a_2}, \ a_2 < x \le a_3 \\ 1, \text{otherwise} \end{cases} \quad (3)$$

Where $\alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \in [0,1], a_1, \ a_2, a_3 \in \mathbb{R}$ and $a_1 \le a_2 \le a_3$.

Definition 4 ([13-15]) : Given$\tilde{a} = \langle (a_1, a_2, a_3); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle$ and$\tilde{b} = \langle (b_1, b_2, b_3); \alpha_{\tilde{b}}, \beta_{\tilde{b}}, \gamma_{\tilde{b}} \rangle$ two single-valued triangular neutrosophic numbers andλ any non-zero number on the real line. Then, the following operations are defined:

1. Addition: $\tilde{a} + \tilde{b} = \langle (a_1 + b_1, a_2 + b_2, a_3 + b_3); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle$,

2. Subtraction: $\tilde{a} - \tilde{b} = \langle (a_1 - b_3, a_2 - b_2, a_3 - b_1); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle$,

3. Investment: $\tilde{a}^{-1} = \langle ({a_3}^{-1}, {a_2}^{-1}, {a_1}^{-1}); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle$, where $a_1, a_2, a_3 \neq 0$.

4. Multiplication by a scalar number:

$$\lambda\tilde{a} = \begin{cases} \langle (\lambda a_1, \lambda a_2, \lambda a_3); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle, \lambda > 0 \\ \langle (\lambda a_3, \lambda a_2, \lambda a_1); \alpha_{\tilde{a}}, \beta_{\tilde{a}}, \gamma_{\tilde{a}} \rangle, \lambda < 0 \end{cases}$$

5. Division of two triangular neutrosophic numbers:

$$\frac{\tilde{a}}{\tilde{b}} = \begin{cases} \langle \left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}\right); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle, a_3 > 0 \text{ and } b_3 > 0 \\ \langle \left(\frac{a_3}{b_3}, \frac{a_2}{b_2}, \frac{a_1}{b_1}\right); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle, a_3 < 0 \text{ and } b_3 > 0 \\ \langle \left(\frac{a_3}{b_1}, \frac{a_2}{b_2}, \frac{a_1}{b_3}\right); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle, a_3 < 0 \text{ and } b_3 < 0 \end{cases}$$

6. Multiplication of two triangular neutrosophic numbers:

$$\tilde{a}\tilde{b} = \begin{cases} \langle (a_1 b_1, a_2 b_2, a_3 b_3); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle, \ a_3 > 0 \text{ and } b_3 > 0 \\ \langle (a_1 b_3, a_2 b_2, a_3 b_1); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle, a_3 < 0 \text{ and } b_3 > 0 \\ \langle (a_3 b_3, a_2 b_2, a_1 b_1); \alpha_{\tilde{a}} \wedge \alpha_{\tilde{b}}, \beta_{\tilde{a}} \vee \beta_{\tilde{b}}, \gamma_{\tilde{a}} \vee \gamma_{\tilde{b}} \rangle, a_3 < 0 \text{ and } b_3 < 0 \end{cases}$$

Where,$\wedge$ it is a ty norm$\vee$ it is a conorm t.

The AHP technique begins with the designation of a hierarchical structure, where the elements at the top of the tree are more generic than those at the lower levels. The main leaf is unique and denotes the objective to be achieved in decision-making.

The level immediately below this contains the sheets representing the criteria. The sheets corresponding to the subcriteria appear immediately below this level , and so on. The level below this level represents the alternatives. See Figure 1.

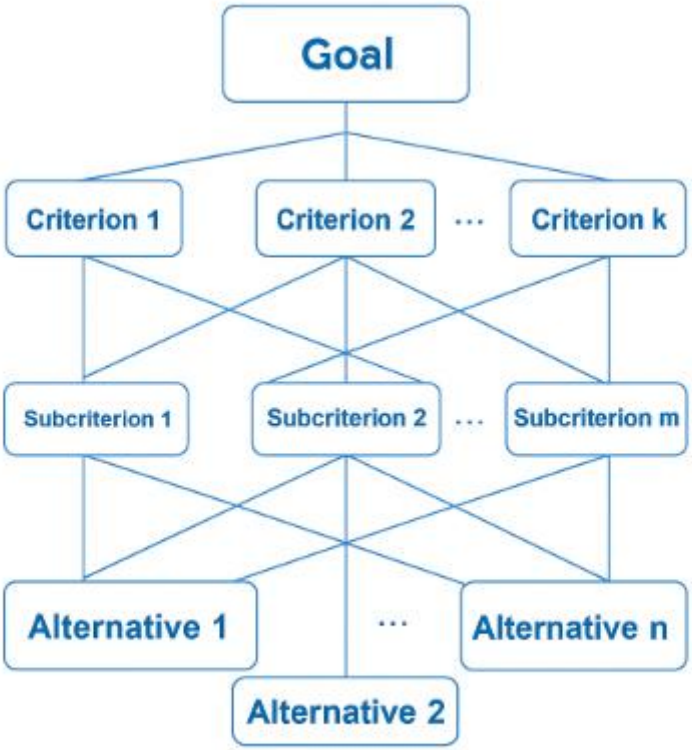

Figure 1 : Generic tree diagram representing a Hierarchical Analytical Process. Source: [16].

A square matrix is then formed that represents the opinion of the expert or experts and contains the pairwise comparison of the assessments of the criteria, subcriteria and alternatives.

TL Saaty, the founder of the original method, proposed a linguistic scale that appears in Table 1.

Table 1: Intensity of importance according to the classic AHP. Source [16-19].

Intensity of importance on an absolute scale	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective.
3	Moderate importance of one over the other	Experience and judgment strongly favor one activity over another.
5	Importance essential or strong	Experience and judgment strongly favor one activity over another.

7	importance very strong	The activity is strongly favored and its mastery is demonstrated in practice.
9	Extremely important	The evidence that favors one activity over another is of the highest order of affirmation possible.
2, 4, 6, 8	Intermediate values between the two adjacent judgments.	When needed comprehension
Reciprocals	If activity *i* has one of the above numbers assigned compared to activity *j* , then *j* has the reciprocal value compared to *i* .	

On the other hand, Saaty established that the *Consistency Index* (CI) should depend on λ_{max}, the maximum eigenvalue of the matrix. He defined the equation $CI = \frac{\lambda_{max}-n}{n-1}$, where n is the order of the matrix. He also defined the *Consistency Ratio* (CR) with the equation CR = CI/RI, where RI is given in Table 2 .

Table 2: RI associated with each order.

Order (n)	1	2	3	4	5	6	7	8	9	10
Rhode Island	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

If CR≤10%we can consider that the experts' assessment is sufficiently consistent and therefore we can proceed to use AHP.

The objective of the AHP is to rank the criteria, subcriteria, and alternatives according to a score. It can also be used in group decision-making problems. If this is the purpose, Equations 4 and 5 should be taken into account, where the expert's weight is evaluated based on their authority, knowledge, experience, etc.

$$\bar{x} = \left(\prod_{i=1}^{n} x_i^{w_i}\right)^{1/\sum_{i=1}^{n} w_i} (4)$$

If $\sum_{i=1}^{n} w_i = 1$, that is, when the expert's weights add up to one, Equation 4 becomes Equation 5,

$\bar{x} = \prod_{i=1}^{n} x_i^{w_i}$(5)

The hybridization of AHP with neutrosophic set theory was used in [16]. This is a more flexible approach to modeling uncertainty in decision-making. Indeterminacy is an essential component that must be assumed in real-world organizational decisions.

Table 3 contains the adaptation of the Saaty scale to the neutrosophic field.

Table 3: The Saaty scale was translated into a neutrosophic triangular scale. Source [16].

Saaty scale	**Definition**	**Neutrosophic Triangular Scale**
1	Likewise influential	$\tilde{1} = \langle(1,1,1); 0.50, 0.50, 0.50\rangle$
3	Slightly influential	$\tilde{3} = \langle(2,3,4); 0.30, 0.75, 0.70\rangle$
5	Strongly influential	$\tilde{5} = \langle(4,5,6); 0.80, 0.15, 0.20\rangle$
7	Very influential	$\tilde{7} = \langle(6,7,8); 0.90, 0.10, 0.10\rangle$
9	Absolutely influential	$\tilde{9} = \langle(9,9,9); 1.00, 1.00, 1.00\rangle$
2, 4, 6, 8	Sporadic values between two close scales	$\tilde{2} = \langle(1,2,3); 0.40, 0.65, 0.60\rangle$
		$\tilde{4} = \langle(3,4,5); 0.60, 0.35, 0.40\rangle$
		$\tilde{6} = \langle(5,6,7); 0.70, 0.25, 0.30\rangle$
		$\tilde{8} = \langle(7,8,9); 0.85, 0.10, 0.15\rangle$

The pairwise neutrosophic comparison matrix is defined in Equation 6.

$$\tilde{A} = \begin{bmatrix} \tilde{1} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \vdots & & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{1} \end{bmatrix} \quad (6)$$

$\tilde{A}$ satisfies the condition $\tilde{a}_{ji} = \tilde{a}_{ij}^{-1}$, according to the inversion operator defined in Definition 4 .

In [20] Two indices are defined to convert a neutrosophic triangular number into a sharp number. See Equation 7 for the *score* and Equation 8 for *accuracy*.

$S(\tilde{a}) = \frac{1}{8}[a_1 + a_2 + a_3](2 + \alpha_{\tilde{a}} - \beta_{\tilde{a}} - \gamma_{\tilde{a}})$(7)

$A(\tilde{a}) = \frac{1}{8}[a_1 + a_2 + a_3](2 + \alpha_{\tilde{a}} - \beta_{\tilde{a}} + \gamma_{\tilde{a}})$(8)

The algorithm to be applied to the NAHP is as follows:

Given the Criteria, subcriteria and alternatives, the NAHP consists of the following steps:

1. Design an AHP tree. It contains the selected criteria, subcriteria , and alternatives.

2. Create the level matrices from the AHP tree, according to expert criteria expressed in neutrosophic triangular scales and respecting the matrix scheme of Equation 6.

3. To evaluate the consistency of these matrices , convert the elements of $\tilde{A}$ in a crisp matrix by applying Equation 7 or 8 and then testing the consistency of this new crisp matrix .

4. Follow the other steps of a classic AHP.

5. Equation 7 or 8 is applied to convert, $w_1, w_2, \ldots, w_n$ to crisp weights.

6. If more than one expert performs the assessment, then $w_1, w_2, \ldots, w_n$ are replaced by $\bar{w}_1, \bar{w}_2, \cdots, \bar{w}_n$, which are their corresponding weighted geometric mean values, see Equations 4 and 5 .

3. Results and Discussion.

Identification of Relevant Socio-Emotional Factors

This section presents the socioemotional factors identified as relevant to student well-being in the context of medical education using AI. For this identification, five experts in medical education and educational technology were consulted, selected for their experience implementing AI tools in health sciences academic programs. The socioemotional factors (SEFs) identified were:

FSE1 > Anxiety about technological dependence : Students' concerns about their ability to function professionally without the constant support of AI tools, generating insecurity about their autonomous clinical skills.

FSE2 > Deterioration of interpersonal communication skills : The reduction in opportunities for direct interaction between students and with real patients due to the intensive use of simulators and digital platforms can affect the development of essential communication skills.

FSE3 > Loss of medical empathy : The risk of dehumanizing the learning process when students become accustomed to interacting primarily with artificial systems rather than real people, affecting their empathic capacity.

FSE4 > Technological adaptation stress : The emotional pressure students experience from constantly mastering new AI tools and staying up-to-date in a rapidly evolving technological environment.

FSE5 > Academic Social Isolation : The trend toward individual learning through AI platforms can reduce the natural social interactions of the academic environment, affecting the sense of belonging and collaboration.

FSE6 > Clinical Decision-Making Insecurity : Students' concerns about their ability to make independent medical decisions without the assistance of AI systems, especially in critical or unforeseen situations.

FSE7 > Cognitive information overload : The stress generated by the unlimited access to information provided by AI tools can be overwhelming, hindering students' ability to synthesize and critically analyze.

Neutrosophic Assessment Methodology

Each of the 5 specialists evaluated these factors using the triangular neutrosophic scale in Table 3. To ensure fairness in the decision-making process, each specialist was given the same weight of importance:$wi = 1/5 = 0.2$.

Expert Evaluation Process

Step 1: Individual Evaluation by Specialist

Each specialist constructed their neutrosophic comparison matrix in pairs according to their knowledge and experience.

Step 2: Converting to Crisp Matrices

The neutrosophic matrices were converted to sharp matrices by applying the accuracy equation 8:$\boldsymbol{A}(\tilde{a}) = \mathbf{1/8}\,\boldsymbol{a}_1 + \boldsymbol{a}_2 + \boldsymbol{a}_3$

Step 3: Consistency Check

The Consistency Ratio (CR) was calculated for each matrix, verifying that$CR \leq 10\%$.

Step 4: Weight Aggregation

Individual weights were aggregated using the simple arithmetic mean, since all experts have the same weight.($wi = 0.2$).

Expert Comparison Matrices

Table 4: Neutrosophic pairwise comparison matrix - Expert 1

Variable	FSE1	FSE2	FSE3	FSE4	FSE5	FSE6	FSE7
FSE1	1	2	1/2	3	2	1/3	1/2
FSE2	1/2	1	3	2	3	1/2	2
FSE3	2	1/3	1	1/2	1	3	3
FSE4	1/3	1/2	2	1	1/2	2	1

FSE5	1/2	1/3	1	2	1	1/2	1/3
FSE6	3	2	1/3	1/2	2	1	2
FSE7	2	1/2	1/3	1	3	1/2	1

Table 5: Neutrosophic pairwise comparison matrix - Expert 2

Variable	FSE1	FSE2	FSE3	FSE4	FSE5	FSE6	FSE7
FSE1	1	1/3	2	1/2	3	1	2
FSE2	3	1	3	2	2	3	1/2
FSE3	1/2	1/3	1	1/3	1/2	2	1
FSE4	2	1/2	3	1	1	1/2	3
FSE5	1/3	1/2	2	1	1	1/3	2
FSE6	1	1/3	1/2	2	3	1	1/2
FSE7	1/2	2	1	1/3	1/2	2	1

Table 6: Neutrosophic pairwise comparison matrix - Expert 3

Variable	FSE1	FSE2	FSE3	FSE4	FSE5	FSE6	FSE7
FSE1	1	2	1/3	2	1	1/2	3
FSE2	1/2	1	2	1/3	3	2	1
FSE3	3	1/2	1	2	1/2	3	2
FSE4	1/2	3	1/2	1	2	1/3	1/2
FSE5	1	1/3	2	1/2	1	1	1/3
FSE6	2	1/2	1/3	3	1	1	2
FSE7	1/3	1	1/2	2	3	1/2	1

Table 7: Neutrosophic pairwise comparison matrix - Expert 4

Variable	FSE1	FSE2	FSE3	FSE4	FSE5	FSE6	FSE7
FSE1	1	1/2	3	1	2	1/3	1/2

FSE2	2	1	2	3	1/2	2	3
FSE3	1/3	1/2	1	1/2	1/3	1	2
FSE4	1	1/3	2	1	3	1/2	1
FSE5	1/2	2	3	1/3	1	2	1/2
FSE6	3	1/2	1	2	1/2	1	3
FSE7	2	1/3	1/2	1	2	1/3	1

Table 8: Neutrosophic pairwise comparison matrix - Expert 5

Variable	FSE1	FSE2	FSE3	FSE4	FSE5	FSE6	FSE7
FSE1	1	1/3	1/2	2	1	2	1/3
FSE2	3	1	1/3	1/2	2	1	2
FSE3	2	3	1	1	1/2	1/2	1
FSE4	1/2	2	1	1	1/3	3	2
FSE5	1	1/2	2	3	1	1/2	1
FSE6	1/2	1	2	1/3	2	1	1/2
FSE7	3	1/2	1	1/2	1	2	1

Consistency Calculations

Expert 1:

- $\lambda max = 7.486321$
- $CI = (7.486321 - 7)/(7 - 1) = 0.486321/6 = 0.081053$
- $CR = 0.081053/1.35 = 0.060039 = 6.0039\%$

Expert 2:

- $\lambda max = 7.592847$
- $CI = (7.592847 - 7)/(7 - 1) = 0.592847/6 = 0.098808$
- $CR = 0.098808/1.35 = 0.073191 = 7.3191\%$

Expert 3:

- $\lambda max = 7.428165$
- $CI = (7.428165 - 7)/(7-1) = 0.428165/6 = 0.071361$
- $CR = 0.071361/1.35 = 0.052823 = 5.2823\%$

Expert 4:

- $\lambda max = 7.739254$
- $CI = (7.739254 - 7)/(7-1) = 0.739254/6 = 0.123209$
- $CR = 0.123209/1.35 = 0.091266 = 9.1266\%$

Expert 5:

- $\lambda max = 7.521836$
- $CI = (7.521836 - 7)/(7-1) = 0.521836/6 = 0.086973$
- $CR = 0.086973/1.35 = 0.064424 = 6.4424\%$

All of which $CR \leq 10\%$,is why the evaluations are consistent.

Weight Calculation by Expert

Table 9: Weights obtained for each variable by expert

Expert/Variable	FSE1	FSE2	FSE3	FSE4	FSE5	FSE6	FSE7
1	0.142853	0.196475	0.178426	0.125847	0.089654	0.164238	0.102507
2	0.158743	0.224619	0.098537	0.173952	0.115684	0.128741	0.099724
3	0.169285	0.153847	0.187354	0.108726	0.105893	0.165248	0.109647
4	0.134926	0.205387	0.087459	0.143785	0.156239	0.174853	0.097351
5	0.119486	0.168542	0.154873	0.147265	0.142968	0.132541	0.134325

Calculation of Final Aggregate Weights

To obtain the total vector of weights considering the five experts, we calculate the arithmetic mean of the weights assigned by each expert to each variable:

Detailed calculations:

$$\boldsymbol{FSE1}: (0.142853 + 0.158743 + 0.169285 + 0.134926 + 0.119486) / 5 = 0.725293 / 5 = 0.145059$$

$\boldsymbol{FSE2}$: $(0.196475 + 0.224619 + 0.153847 + 0.205387 + 0.168542) / 5 = 0.948870 / 5 = 0.189774$

$\boldsymbol{FSE3}$: $(0.178426 + 0.098537 + 0.187354 + 0.087459 + 0.154873) / 5 = 0.706649 / 5 = 0.141330$

$\boldsymbol{FSE4}$: $(0.125847 + 0.173952 + 0.108726 + 0.143785 + 0.147265) / 5 = 0.699575 / 5 = 0.139915$

$\boldsymbol{FSE5}$: $(0.089654 + 0.115684 + 0.105893 + 0.156239 + 0.142968) / 5 = 0.610438 / 5 = 0.122088$

$\boldsymbol{FSE6}$: $(0.164238 + 0.128741 + 0.165248 + 0.174853 + 0.132541) / 5 = 0.765621 / 5 = 0.153124$

$\boldsymbol{FSE7}$: $(0.102507 + 0.099724 + 0.109647 + 0.097351 + 0.134325) / 5 = 0.543554 / 5 = 0.108711$

Final Result: Ranking of Socio-Emotional Factors

Total weight vector for variables FSE1 to FSE7:

- $FSE1$: 0.145059
- $FSE2$: 0.189774 ← **PRIORITY 1**
- $FSE3$: 0.141330
- $FSE4$: 0.139915
- $FSE5$: 0.122088
- $FSE6$: 0.153124
- $FSE7$: 0.108711

Final ranking: $\boldsymbol{FSE2 > FSE6 > FSE1 > FSE3 > FSE4 > FSE5 > FSE7}$

Interpretation and Analysis of Results

The results of the neutrosophic analysis reveal a clear hierarchy of socio-emotional factors that require priority attention in the implementation of AI in medical training:

High Priority Factors

1. Deterioration of interpersonal communication skills (FSE2 - 18.98%) This factor emerges as the main concern, reflecting the expert consensus on the fundamental importance of maintaining and developing communication skills in medical training. Effective communication constitutes an essential pillar of medical practice, and its deterioration due to the intensive use of AI technologies represents a significant risk to the quality of healthcare.

2. Insecurity in clinical decision-making (FSE6 - 15.31%) The second priority underscores the importance of maintaining professional autonomy and trust in clinical judgment. Future physicians must develop the ability to make independent and critical decisions, using AI as a support tool without relying excessively on it.

Medium-High Priority Factors

3. Anxiety about technological dependence (FSE1 - 14.51%) This factor reflects the need to balance the use of technological tools with the development of autonomous clinical skills, preparing students for situations where technology may not be available.

4. Loss of medical empathy (FSE3 - 14.13%) Although it ranks fourth, preserving medical empathy remains crucial to maintaining the human aspect of medicine, especially in a context of increasing digitalization.

Implications for Medical Education

The results suggest that educational institutions should:

1. **Prioritize the development of communication skills** through strategies that combine technology with real human interactions.
2. **Strengthen confidence in clinical judgment** through learning experiences that encourage independent and critical decision-making.
3. **Implement technology balancing programs** that avoid over-reliance on AI tools.
4. **Maintain the empathic component** in all educational activities, ensuring that technology complements, not replaces, human connection in medicine.

The NAHP analysis has provided a quantitative and structured understanding of the most critical socioemotional factors in the integration of AI into medical training. The deterioration of interpersonal communication skills emerges as the primary concern, followed by uncertainty in clinical decision-making.

These findings underscore the need to design educational strategies that balance technological innovation with the fundamentally human aspects of medical practice. Educational institutions must develop curricular frameworks that leverage the benefits of AI while preserving and strengthening the socioemotional competencies essential for compassionate and effective medical practice.

Neutrosophic methodology has proven particularly valuable in capturing the uncertainty and complexity inherent in expert perceptions of these emerging topics, providing a solid basis for informed educational decision-making in the context of the digital transformation of medical education.

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