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PAPER

An Intelligent Mathematics Problem-Solving Tutoring System Framework: A Conceptual of Merging of Fuzzy Neural Networks and Neuroscience Mechanistic

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ABSTRACT

This study proposed a novel framework for redesigning problem-solving activities in an intelligent tutoring system (ITS) called the intelligent neural-mechanistic mathematics problem-solving tutoring system (IN-MP-STS). This concept paper presents a new approach to ITS by incorporating elements of neuroscience mechanisms as a learning strategy that focuses on optimizing the brain's ability through neural mechanisms. It also introduces fuzzy neural networks (FNNs) as a tool for modulating assessment and analyzing outcomes. This framework offers an alternative perspective on delivery methods and learning approaches in the ITS module. By effectively integrating neuroscience mechanistic elements such as motivation, activation, regulation, execution, memorization, and interactivities, deep learning can be achieved, leading to improved student competence. This framework also proposes an adaptive assessment component based on FNNs, which will enhance the measurement and feedback modules in the system. It is necessary to modify the way that ITS and soft computing methods, such as the study of neural networks (NNs), are combined to make learning measurement and assessment more transparent. This innovation has not been fully disclosed, so researchers are encouraged to further test the concepts presented to assess their alignment with the existing system and ethical considerations. This framework enhances the conceptual research findings of FNNs and incorporates neuroscience-based strategies into architecture and autonomous problem-solving skills within an ITS model. It also offers references for the development of problem-solving learning. IN-MP-STS has the potential to significantly enhance students' competencies and abilities, thereby fostering the development of more comprehensive, holistic, and sustainable ITS. This approach also has the potential to enrich the existing literature on the sustainability of neural networks.

KEYWORDS

mathematics problem-solving, neuroscience mechanistic, fuzzy neural networks (FNNs), intelligent tutoring system (ITS), deep learning

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1 INTRODUCTION

The latest technological advancements have transformed and minimized various challenges in the administration of education and instruction. One technology application that enhances the efficiency of learning management is the intelligent tutoring system (ITS). ITSs are computerized systems that provide personalized learning by reducing the need for direct guidance from the teacher. The use of ITS is more frequent during epidemics. ITSs are the preferred choice because they are more suitable for implementing learning without the need for physical meetings. However, issues and annoyances arise when discussions about learning outcomes and effectiveness begin. It is more critical when the ITS system is designed for individualized learning without direct guidance from the teacher to monitor progress. The question that is often raised is whether the ITS system is designed to help students achieve deep learning. [1] voiced criticism of ITS, heralded as "smart" pedagogy. However, what happened was a failure to cultivate deep learning in students. Furthermore, [2] suggests that the ITS system should be more user-friendly and equipped with specific features that are adaptive, multimedia, and, most importantly, capable of enhancing students' abilities. In this context, the development of computational neuroscience and soft computing techniques has generated new ideas and brought about a transformation in ITS. Among other things, this combination aims to strengthen the ITS system, particularly by enhancing the interaction between students, the social environment, and the curriculum with the system itself [3].

In essence, deep learning is the outcome of students' interaction with the learning environment, materials, and teaching methods, or the delivery medium, which influence emotions, behavior, and cognition. According to [4], deep learning can occur when there is a shift in cognitive characteristics and behavior, which can be clearly recognized and interpreted, and even when students receive feedback on the change. In conventional learning, the teacher serves as a monitor and assessor, and all learning feedback is based on the teacher's interpretation. However, in ITS, this does not happen because the system is developed based on an individualized learning environment without guidance. In addition, in ITS, aspects of pedagogy that aim to evoke prior learning are challenging to prepare because they are closely linked to students' deep learning [5]. This weakness is attributed to the absence of translation, evaluation, and interpretation for every action and achievement completed by students. There is a gap between the concept and practical application of ITS. In theory, this pedagogy is perceived as "smart," but in reality, it is not very effective in fully developing the potential and creativity of students [2]. Therefore, this ITS needs modification to ensure that deep learning takes place, with a focus on fostering a sense of belonging and honesty in the learning process.

Therefore, this system requires a "facilitator" who can act as a teacher's assistant by tracking, monitoring, and providing learning feedback. With the latest innovation, this role has been taken over by intelligent computerized systems, as previously mentioned, such as artificial intelligence (AI) or machine learning (ML). One of the primary objectives of employing soft computing in ITS is to enhance the capabilities of recognition, monitoring, and evaluation [3, 6]. Some studies demonstrate the positive outcomes of integrating ITS and computational intelligence (CI), as evidenced by research conducted by [7–9]. The application of neural networks (NNs) has a positive impact on the development of ITS, particularly in facilitating the teaching and mastery of challenging and crucial subjects or skills such as engineering, mathematics, language, and problem-solving tasks. [10, 11] successfully implemented NNs and developed a more advanced learning management system. However, the efficiency of NNs depends on the type, source, and orientation of the data. The data entered into the NNs site must consist of accurate parameters or attributes in order to produce clear output and achieve the intended objective. The complexity of the data source that describes learning necessitates the use of an appropriate structure or architecture for the NN algorithm. In this context, fuzzy NNs (FNNs) were chosen because of their adaptability to a variety of orientations and data sources, as evidenced by several researchers [12–17].

Problem-solving in mathematics is an example of a complex learning environment. Problem-solving is inherently challenging and requires specific cognitive and behavioral abilities [18, 19]. As a result, the delivery medium must be diverse and not limited to traditional methods. ITS can be used to support experimentation and improvement in problem-solving teaching in mathematics. Why is problem-solving important in mathematics? Why is ITS used? What does this have to do with FNNs? These questions will be addressed and will require further discussion. Problem-solving is both a skill and a measure of one's competence level. In the context of education, problem-solving skills are integrated into the curriculum and must be mastered by students. The problem-solving domain is utilized as a benchmark for mastery standards and learning trends in international programs such as TIMSS and PISA [20, 21]. Numerous researchers have confirmed and explained the significance of problem-solving in determining the success of the mathematics curriculum [22–24]. Therefore, there is a need to strengthen the learning of mathematical problem-solving. One approach is to implement an ideal learning management system, such as an ITS. However, the weaknesses and gaps in the development of ITS, as discussed earlier, need to be resolved first. Discussions and arguments in previous studies indicate that the implemented ITS pedagogy does not fully develop students' potential for perfecting problem-solving [2, 11, 15, 17, 25–27].

Competence in solving mathematical problems is crucial, so their presentation needs to be managed efficiently and effectively. All attributes (factors) related to competence, whether they demonstrate strengths or weaknesses, need to be analyzed and interpreted accordingly [19, 28–30]. To describe the attribute, a smart and efficient feedback system is required. Therefore, FNNs are the optimal choice for recognition, assessment, and feedback. The efficiency of FNNs depends on the fusion of data, as mentioned previously. Because learning and the process of solving mathematics problems are highly complex, the measurement and assessment of learning require specific details. This systematic detail will serve as the input for the FNN system, resulting in clear output and the achievement of objectives. The discovery and exploration of neuroscience knowledge, particularly in the field of learning, has revealed how the learning process occurs. Systematic literature by [31] explains the gap in educators' understanding of the potential of neuroscience-mechanistic strategies in enhancing students' learning abilities. The previous studies discussed showed a positive impact when implementing neuroscience mechanistic strategies, but there was a gap between knowledge and practice among educators. Neuroscientific mechanistics is the stage of the development of mechanisms or processes that occur in the context of neural connections, manifested by the nature of neuroplasticity or neurotransmitters in parts of the brain, to form certain knowledge or skills.

As discussed, the effectiveness and impact of the FNN application depend on the entered data. Therefore, it is very appropriate to use the elements of neuroscience mechanisms as attributes in the identification, assessment, prediction, and feedback system of the learning process. Neuroscience delves into the mechanisms of learning in great detail, exploring the beginning and ending, external and internal factors, and even cognitive and behavioral development. According to the conceptual model introduced by [32], the neuroscience mechanistic attributes that can influence mathematics learning include motivation, attention, activation, regulation, implementation, and evaluation. These attributes can predict students' deep learning. This conceptual model is based on a neuroscience model, namely the AGES Model introduced by [33], which is founded on four main constructs: attention, deneration, emotion, and spacing. Therefore, this study is particularly suitable for bridging the gap between neuroscience and the learning environment in the classroom.

In conclusion, based on the problems discussed, the researcher believes that there is a need to develop a more ideal framework for modifying ITS indicators to enhance problem-solving skills. This modification will involve a combination of FNNs and neuroscience mechanistic strategies to enhance the human-centric effects of the intelligent engineering system of ITS. Therefore, the objective of this study is to propose a new framework for redesigning problem-solving activities in ITS, specifically the intelligent neural-mechanistic mathematics problem-solving tutoring system (IN-MP-STS). This paper also offers valuable suggestions, including the design of problem-solving learning activities and research methods. The following are the main contribution points of this paper:

1. This paper presents a new problem-solving learning framework that is based on FNNs and neuroscience mechanistic strategies. First, it gathers and organizes neural mechanisms related to the learning process. Secondly, it utilizes FNNs to create evaluations of problem-solving learning activities in order to achieve personalized teaching and learning resources, which can enhance the quality of problem-solving tutoring.
2. This paper integrates FNNs with a neuroscience-based mechanistic approach to propose a framework for problem-solving learning activities. The framework utilizes FNNs to structure and extract local features from the active learning process, and it is based on the mechanistic cognitive and learning behavior of the student.

Continuing from this, the next section will discuss the relationship between problem-solving theory and educational neuroscience theory, describing their interconnection. Next, there is a section that will explain the necessity of the new design for the problem-solving activity. This justification involves the development of NNs and mechanistic strategies in neuroscience. The following section pertains to the methodology and outlines how this study was conducted, including the conceptual design of the introduced framework.

2 NEUROSCIENCE AND PROBLEM-SOLVING VIEWS

Discussions about deep learning need to be based on various theories and perspectives, such as constructivist, information processing, and neuroscience views. It is the science of studying learning processes and issues over time. This development also addressed details and issues related to definitions, theories, and models in problem-solving. According to [34], problem-solving theories are strengthened through numerous studies that focus on the "internal" aspect, specifically the cognitive processes involved in problem-solving activities. It was first discussed by [35] in his theory, which describes how individual mental processes occur during problem-solving activities. The emphasized elements include readiness for knowledge, experience, metacognition, and self-belief [24]. [36] On the other hand, it emphasizes that the problem-solving process requires optimal self-motivation along with the ability to manage cognitively. According to [37], three models, namely the Newell and Simon Model (1972), the Schoenfeld Model (1985), and the Mayer Model (1985), are the initiators and founders of more complex models that involve computer programming, such as NNs, simulator programs, and learning-based multimedia. The discovery of neuroscience also bolsters the theory of problem-solving, based on an understanding of the human brain's mechanisms involved in learning [38, 39].

The OECD publication in 2004 on problem-solving for tomorrow's world, discussed issues related to the definition of problem-solving competence as the ability of individuals to use cognitive skills to understand challenging situations and to formulate solutions when there is no easy answer [40]. Among other aspects, solving mathematical problems is defined by some researchers as the combination of knowledge, abilities, and mathematical skills [20], as well as cognitive processes, metacognitive skills, and neurocognitive implications for mathematical problem-solving [24]. The definition of problem-solving can be summarized as a series of cognitive processes that involve repetitive actions, mental processes, and follow-up steps. It encompasses specific steps that engage both external and internal actions, utilizing sensory, nerve, and brain functions. For instance, students encounter challenging situations (tasks) by reading problems visually, processing information through neural and brain mechanisms, and then taking action to solve them, enabling them to write and respond to the problems presented.

According to [24], problem-solving is a systematic and planned action, so it is related to or requires a certain motivation that drives students' work. The researcher believes that to comprehend how students solve problems, it is preferable to examine the mechanisms involved. The researcher described the process of students solving problems as a structured and mechanistic one that includes several levels of mechanisms. Starting with the student's self-regulation, including attitude, motivation, and willingness to perform tasks. The second aspect is the operating mechanism, which involves understanding problems, selecting strategies, deepening knowledge, making decisions, and organizing solutions. This mechanism refers to the processing and functionality of the brain, or it can be referred to as neurocognitive. Next, the third mechanism is integration, where the operating mechanism is combined with the relevant knowledge terms, topics, or concepts to complete problem-solving.

In conclusion, the solution to this problem involves a mechanistic approach rooted in neuroscience that considers both the external and internal aspects of the student, as discussed in studies by [41–45]. This opinion is based on factors such as emotion, motivation, readiness, belief, cognitive and metacognitive processes and is related to the constructs of neuroscience. According to researchers in the field of educational neuroscience, learning and problem-solving are influenced by the activity and functionality of specific parts of the brain that have distinct effects. A report by [46] shows that the frontal, occipital, temporal, and other areas of the brain will be active when students start reading and interpreting numbers. According to [44], pleasure and willingness to solve problems are linked to the functionality of the amygdala and the prefrontal cortex. Next, to ensure successful problem-solving, the activity and strength of neural networks in parts such as the left frontal and parietal lobes are crucial. These networks contribute to building working memory, processing speed, execution, insight, and other cognitive functions [19, 47, 48].

3 NEURAL NETWORKS AND NEUROSCIENCE MECHANISTIC STRATEGIES TO PROMOTE MATHEMATICS PROBLEM-SOLVING LEARNING

Biological models of communication systems and neural networks have been developed into mathematical models that represent the behavior of neurons as they form a chain or a specific relationship, producing a specific pattern known as network architecture. An artificial neuron, known as a perceptron, is a single processing unit that forms the basis of NN models, drawing from the fundamental properties of biological neurons. Their function is analogous to that of biological neurons, processing multiple signals as input. Modification of the input signal can be achieved by applying a weight to the receiving synapse. Next, the processor will sum the weighted inputs and activate the spread function. The neuron receives meaningful and adequate input and sends it as a single output, typically connecting to many other neurons, similar to the axon branch of a biological neuron. This model serves as the foundation for developing neural network models in the field of AI or ML, such as fuzzy neural networks.

Returning to the architecture of biological neural networks, this concept forms the basis of the learning process. This discovery is a study of how deep learning and thinking processes occur in the brain and are interpreted, known as cognitive science or neuroscience models. Overall, this model describes the mechanistic operation in learning, which is a strategy or approach that explains the relationship between the senses and specific parts of the brain. In learning or solving problems, students use their senses to comprehend the situation (task) and assign meaning to the problem. Actions such as reading texts, recognizing pictures, diagrams, graphs, symbols, and so on, are performed to identify the presented issues [49]. In other words, students will derive meaning from the instructions and structure of the task [19]. During this stage, parallel processing is a mental or neurocognitive process in which information from earlier sources is transmitted through nerves to different parts of the brain for translation, involving memory and cognitive control systems [50]. [19] explained that the neurocognitive mechanism involved in the activation of previous knowledge (memory) is also linked to the formation of emotions towards the task (achievement emotions).

García et al. [47] argue that once students are exposed to the problem (task), they will develop a system or approach to achieve the final result, beginning with the act of reading and researching to gain understanding. [49] describes this process as a way of constructing a problem-situation model based on the mathematical or non-mathematical elements found in the presented problem. [51] demonstrated a direct relationship between reading comprehension and problem-solving abilities. A study report by [19] explains that a clear understanding and definition of the problem (task) will mediate cognitive coordination and evaluation. In this context, students need to understand the problem, including linguistic knowledge, facts, and schematic knowledge [36, 49, 52].

According to [46], letters and digits are detected in various parts of the brain, including the frontal, occipital, and temporal lobes, as well as the left inferior temporal gyrus (ITG). [53] states that this mechanism involves an appreciation of the problem situation (task) that enables students to begin building theory and knowledge. According to [54], students will simultaneously develop a hypothesis or initial conclusion for the solution by engaging in reflective thinking andrecalling memories and skills from previous experiences. A study by [48] has reported that academic performance in this scenario depends on the strength or weakness of the student's working memory system. The results of his research show that working memory has a greater impact on the process of reasoning a solution than on performing a solution or mathematical calculations. The results of this study are also supported by several other research reports that explain the important role of working memory in helping students complete problem-solving tasks, including the processes of visualizing, abstracting, hypothesizing, and estimating the solution [55–58]. Students who have a positive metacognitive experience will develop a smooth and accurate execution process. This situation, according to psychological studies and neuroscience mechanisms, is the result of insight into problem-solving. According to [59], the key feature of insight is completing the mental representation of problem-solving. The speed of calculations and the use of mathematical operations also depend on neural connectivity, which shifts, changes, and adapts according to the represented problem [60]. According to reference [23], when operational characteristics exhibit continuity and repetition, the circuit of execution and insight will yield faster and more accurate results. In addition, as stated in [44], the amygdala and the prefrontal cortex will facilitate the development of the regulatory reward circuit when there is prior experience in solving similar problems that lead to enjoyable achievements.

According to the analysis by [47], problem-solving models indicate that the process of solving problems involves neuroscience and brain function at every stage. Among the models discussed are Polya's model (1981), IDEAL's model (1993), Montague et al. (2000), Pretz et al. (2003), Verschaffel et al. (1999), Zimmerman's SRL model (2008), and Boonen's model (2015). The unity in the model demonstrates the mechanistic aspects of neuroscience that may have either positive or negative effects on students' mathematics problem-solving ability. According to [61], experiencing perfection and pleasure while solving problems generates positive achievement emotions. Neuroscience studies show that this positive emotional effect is effective in shaping interest, readiness, and motivation and reducing anxiety levels for problem-solving and learning [44].

In the context of implementing this neuroscience-based mechanistic strategy, identification and assessment necessitate suitable mathematical analysis. This is because the description and details of each learning mechanism need to be interpreted using an intelligent system so that they can be properly reported. The analysis of NNs is rapidly advancing and being fully utilized in the field of engineering. It should also be integrated into the field of education, particularly in the classroom, as a tool for assessment. [62] Several suggestions have been made for innovating neural networks in classroom assessment, including using variations such as fuzzy analysis and multi-criteria decision-making methods. The architecture of the algorithm in neural networks is highly detailed and sensitive to the orientation of the input data, making it well-suited for recognizing, measuring, and providing feedback in the learning process. One of the most suitable approaches for analyzing neuroscience mechanisms is using FNNs. [14, 15] employ NNs for analysis to evaluate changes and receive feedback on the learning process. It can be concluded that problem-solving skills should be developed using a computerized strategy that incorporates both biological and mathematical NNs, along with a combination of neuroscience concepts such as motivation, emotion, metacognition, working memory, processing speed, execution, and memory, among others.

4 CONCEPTUAL FRAMEWORK OF INTELLIGENT NEURAL-MECHANISTIC MATHEMATICS PROBLEM-SOLVING TUTORING SYSTEM

4.1 Fuzzy neural networks

Fuzzy neural networks are systems that utilize learning algorithms based on neural network theory to process data from specific parameters, which are determined from fuzzy sets and fuzzy rules. FNN is a continuation of NN technology, incorporating diversity in the input layer and output layer [14], and combined with fuzzy logic technology. The combination of these two technologies is so beneficial that it creates a system that is more flexible and even more efficient than applying only one technology. FNNs have been utilized as computing technology in various fields, including the development of control system technology, image recognition, and data mining. Some of the benefits of FNNs include their applicability to both structured and unstructured data, their use in pattern recognition, their ability to handle inaccurate or incomplete data, and their versatility in various applications. The text provides a description of neurons, synapses, weights, biases, and their functionality [14, 16]. This component is an adaptation of the way the human brain processes and functions.

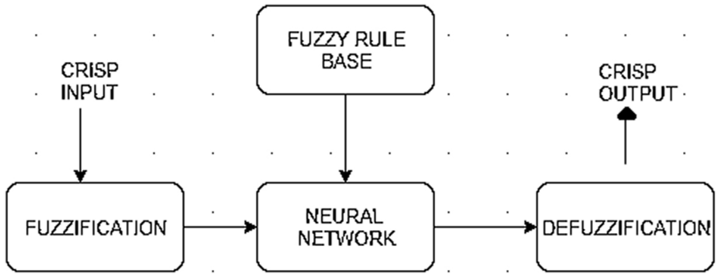

Fig. 1. The structure of a fuzzy neural system

In general, the orientation of FNNs depends on the feed-forward data network, which in turn produces the output from the input layer as shown in Figure 1. FNNs will essentially create a map of neurons and generate random numerical values, or "weights." The weights and inputs are adjusted to produce an output value ranging between 0 and 1. In summary, in the workflow for FNNs refer to Figure 2, each neuron in the input layer sends a signal directly to the next layer to generate an output. Here, each neuron $X_i(i = 1, 2 \ldots N)$ receives an input after assessing the degree to which the input belongs to its set or the magnitude of its weights. For each input variable X_i, M fuzzy sets are defined $A_{im}(m = 1, 2 \ldots M)$ whose membership functions are the activation functions of the corresponding neurons. It can be represented as a set of fuzzy rules at any point in the learning process, whether it is before, during, or after.

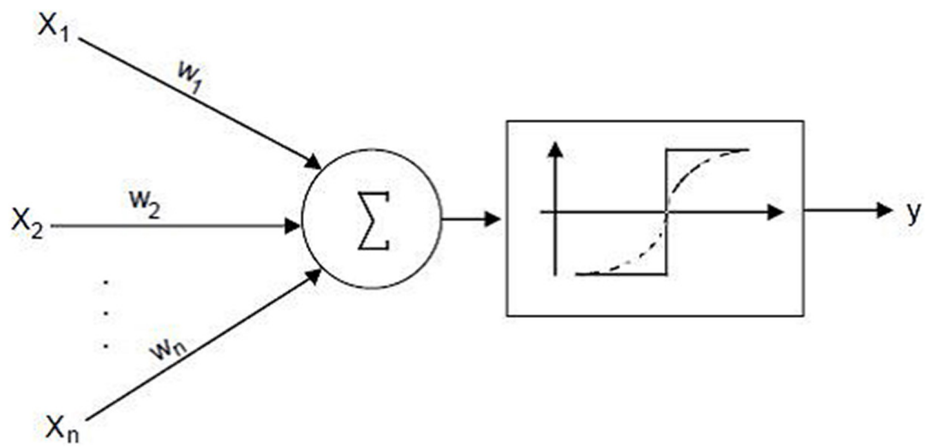

Fig. 2. The architecture of the fuzzy neural network

Then, the neuron combines all the inputs using a fuzzy operation called fuzzification in the second layer. The fuzzification layer is utilized to construct the antecedent of the fuzzy logic rule. The output of the fuzzification layer characterizes the potential distribution of the antecedent clause "X_i *is* A_i". Thus, the outputs of the first layer are the membership degrees associated with the input values, i.e., $a_{im} = \mu A_{im}$ ($i = 1, 2 \ldots N$ and $m = 1, 2 \ldots M$), where N is the number of inputs and M is the number of fuzzy sets for each input. This layer involves the implication process (weighted aggregation), where the neurons contain the product of inputs based on the neuron parameters' weights after being composed by L fuzzy unineuron. This aggregation is performed using the weights, $W_{il}(i = 1, 2 \ldots N$ and $l = 1, 2 \ldots L)$, for each input variable i, which is only one first-layer output a_{im} is defined as the input of the l-th neuron. Next, each neuron is synthesized to produce a single output with the defuzzification method in the last layer, with:

$$y = sign\left(\sum_{i=0}^{L} a_{im} * W_i\right) \tag{1}$$

Where $a_0 = 1$, W_0 is the bias, and a_{im} and W_i, $(i = 1, 2 \ldots L)$ are the output of each fuzzy neuron of the fuzzification layer and their corresponding weight, respectively.

Compared to conventional NNs, the connection weights and activations of FNNs are significantly different. There are numerous approaches to modeling FNNs [16]. Some approaches use five layers, with the fuzzy sets encoded in the units of the second and fourth layers, respectively. FNNs are composed of three different types: cooperative, concurrent, and hybrid FNNs. In this context, FNNs model more complex non-linear relationships. The FNN architecture generates a compositional model based solely on the objective and can define the output as either a concentrated or primitive composition [11]. The algorithm will adjust the weights if the network is unable to accurately estimate certain input patterns [15]. Certain parameters or manipulations of mathematical algorithms will be established to influence and process the provided data.

Various approaches and variations of FNNs are utilized. Among them are four main components: input statistics, objective function, learning algorithm, and network architecture, as discussed by [8] and illustrated in Figure 3.

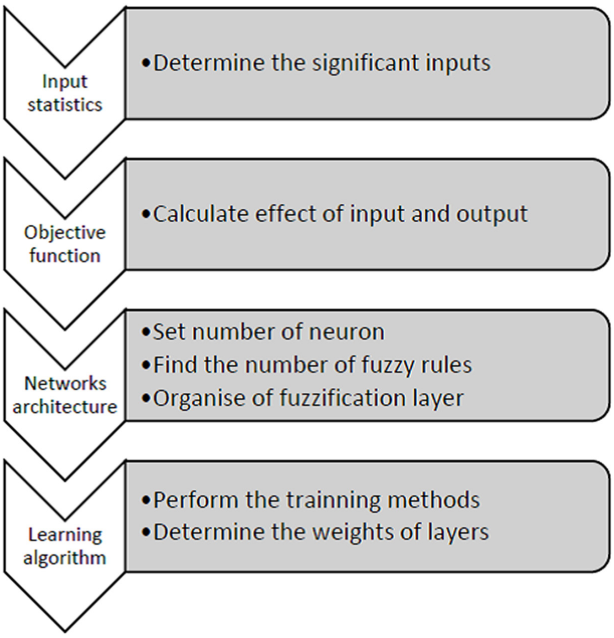

Fig. 3. The components of FNNs

Next, based on these four components, FNNs have been adapted as recognition tools, modeling tools, monitoring boards, assessment tools, and also as learning aids. It is commonly used as a driver in e-learning management systems, such as ITS. The following Table 1 presents a meta-analysis of the modification, method, and manipulation of FNNs as assessment tools for both traditional classroom learning and e-learning platforms.

Table 1. Analysis of application, methods and manipulation of FNNs

Application of FNNs	Objectives	Types/Methods of FNNs	References
Recognition/ Translation	Monitoring students' actions	Neural network-based fuzzy diagnostic	[7]
	To determine the interrelations between LMS evaluation criteria and their effects	Hybrid FNNs-DEMATEL	[63]
	Evaluating the Perceptions of learning statistics among Students	FCM	[64]
	Deciding the factor that ignites student's creativity in an introductory engineering course	Fuzzy Analytic Network Process (FANP)	[65]
	Human hand gesture recognition	Hybrid FNNs-CNN	[10]
	Recognition and Evaluation of Classroom Teaching Behavior	Hybrid FNNs-DNN	[11]
	Recognition of speech and text in English Flip Classroom	Hybrid FNNs-RNN	[17]
Modelling	Generated the training set for a physical activity assessment	Cooperative FNNs	[66]
	To model and predict the equilibrium adsorption of acids at different temperatures	Hybrid FNNs-DNN	[16]
	Establish the model of attitude towards statistic	ANFIS	[67]
	Develop a decision-making model for student	Fuzzy Analytic Network Process (FANP)	[68]
Classification/ Clustering	Assess student performance	Hybrid FNNs-FANP, DEMATEL	[69]
	Identifying and analysing the criteria for e-learning education systems	Hybrid FNNs-DEMATEL	[70]
	Determining the weights of criteria and priority values of multimedia applications	FAHP	[71]
Prediction	Prediction of Student academic performance	Hybrid FNNs-Genetic Algorithm	[72]
		ANFIS	[73]
		Hybrid FNNs-DNN	[14]
	Analyzing pupils' knowledge of mathematics	ANFIS	[74]
	Predicting learning styles	Hybrid FNNs	[75]
	Analyze the weight of influencing factors in Flip Classroom	Hybrid FNNs-DNN	[15]

4.2 Elements of neuroscience mechanistic

To provide a more specific context for the findings of neuroscience, the discussion focuses on several manifestations that contribute to the development of this knowledge. In the context of education and learning, neuroscience focuses on the field of cognitive neuroscience. The expression of neuroplasticity and neuroconnectivity serves as a catalyst for cognitive processes and learning behaviors. In this context, [32] proposed several elements of mechanistic neuroscience that determine and drive learning, particularly in the creation of deep learning as summarized in Table 2. Each of these attributes will establish dimensions and premises that describe cognitive, psychological, and behavioral practices or actions in those elements. These can be used as objects and criteria to measure students' ability to solve mathematics problems.

Table 2. Element of neuroscience mechanistic based on Bakar et al. [32]

Motivation	This characteristic reveals how enthusiastic and interested pupils are in mathematics problems or tasks. Can lead to motivation for oneself. Positivity and great confidence in one's ability to manage a solution.
Attention	Reflection on behaviour that demonstrate willingness and concentration on finding a solution. Know and understand math topics or facts. Be conscious of the brain and memory's capabilities and accomplishments.
Activation	Competently formulates problem objectives and is capable of drawing early decisions regarding a mathematics problem. Can create problem/task abstracts and overviews. Understand how to stimulate and the need to think in terms of the level of difficulties. Capable of creating math operation statements from task sources. Indicate the equation or mathematics formula that will be utilized.
Regulation	Plan mathematics operations, solution strategies, and time allocation to create a problem-solving arrangement circuit (solution flow). Capable of controlling one's thought activity. Control the depth of thought concerning the complexity of the mathematics task. Create connections between prior mathematics problems or concepts, as well as existing knowledge, and the current mathematics task.
Implementation	Carry out mathematical procedures with accuracy and effectiveness. Develop a strategy and keep track of the accuracy and completeness. If you're having trouble, find alternate alternatives quickly. Always upbeat about accomplishments, capable of controlling emotions, and not easily perplexed.
Evaluation	Verify if the solution is correct. Calculations should be evaluated using repetition or looking back. Contrast recent learning findings with prior experience. Create solutions that are similar to guarantee correctness.

4.3 Intelligent tutoring system

An ITS is a blended learning system that relies on computerized instruction to deliver lessons to individuals without the need for physical support from a teacher [7]. In this system, learners will receive feedback on their learning directly. This system is modeled with several main components, namely the domain model, the student model, and the instructional model as shown in Figure 4. For the instructional component, there is also a more detailed breakdown of the tutoring model and user interface model [1, 2, 26].

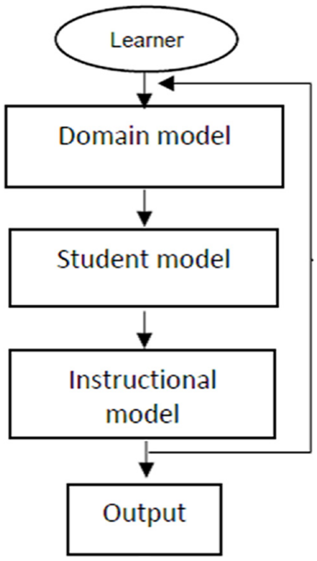

Fig. 4. The basic structure of ITS

The ITS is enhancing learning in a more meaningful and effective way with the guidance of computer technology. Regardless of formal education or higher education, ITS has been widely implemented and has demonstrated various capabilities as well as limitations. This circumstance or situation creates a close relationship between smart technology and learning theory, including cognitive or behavioral aspects, and then produces variations to the design of the system itself [7]. In addition, ongoing research to enhance the effectiveness of ITS is also actively being pursued. Ultimately, the development of modern ITS aims to improve teaching methods and optimize students' abilities to articulate problems, select solutions, and solve problems using a solid knowledge foundation [2].

The model domain is a fundamental component of the ITS system. According to references [1, 6, 26], this is also known as the cognitive model or expert knowledge model. This model is constructed based on learning theory, incorporating a combination of theoretical elements designed to facilitate learning. Furthermore, this component encompasses learning stages, including concepts, rules, and problem-solving strategies within the domain to be learned [2]. This model also serves as a knowledge repository and learning environment and includes a learning assessment mechanism. The follow-up to the domain model is the student model. The emphasis on learning is directly related to the composition of this model. This is because meaningful and profound learning will occur based on is the components available in this model. At this time, the cognitive, behavioral, and affective aspects of students will be integrated and synthesized based on the learning strategy in place. This happens when students apply their problem-solving methods and steps. The arrangement of components typically starts with simple tasks and progresses to more complex ones, necessitating a structured guidance and assistance system for tracking each activity [1, 17].

Next, the instructional model receives information from the domain model and student model, which includes decisions about learning strategies and teaching actions. Here, the focus is on the goal and the subsequent effects of the activity, so the model is developed with suitable activity and tracking methods. The advancement of engineering technology today has highlighted the challenge of accurately translating the true intention of this model. With the assistance of AI systems and ML, various instructional variations can be generated to achieve more practical and effective objectives [2]. However, accurate design is required to achieve specific goals, such as targeted skills. In this context, the design and philosophy of ITS development are subjects of discussion. This is either related to the concept or design. The ITS system has a very unified design, but the learning concept has less impact. On the other hand, it often happens that learning is prioritized, but the design features are not adequate. Therefore, to bridge this gap, ITS with a unique design is required, along with the integration of effective learning strategies as a component of the combined models.

5 REDESIGNING OF PROBLEM-SOLVING TUTORING USING FUZZY NEURAL NETWORKS AND NEURO-SCIENCE MECHANISTIC AND INSTRUCTIONS IN-MP-STS

The concept of IN-MP-STS is based on FNNs and mechanistic neuroscience, which can facilitate learning processes. Problem-solving skills can be improved through effective learning tools, such as the FNNs platform, which includes defining problem-solving, challenging types of competition activities, and presentation activities. There is no single standard practice for implementing theories in deep learning. In this paper, all the theories are listed in Table 3. A conceptual framework of IN-MP-STS is proposed by integrating principles of fuzzy neural networks, neuroscience mechanistic strategies for learning, and components of intelligent tutoring systems.

Table 3. Fuzzy neural networks, neuroscience mechanistic strategy and ITS components

Fuzzy Neural Networks (FNNs)	Neuroscience Mechanistic Strategy [32]	Intelligent Tutoring System (ITS)
1. Input statistics **2.** Objective functions **3.** Learning algorithm **4.** Networks architectures	**1.** Motivation **2.** Attention **3.** Activation **4.** Regulation **5.** Implementation **6.** Evaluation	**1.** Domain model **2.** Student model **3.** Instructional model

The framework is proposed in response to the growing research interest in FNNs and neuroscience practice. At the same time, there is a limited existing framework in ITS, especially in problem-solving tutoring. Therefore, Figure 5 illustrates the general concept of the conceptual framework. The proposed framework consists of seven interconnected mediators. It is believed that integrating these mediators would optimize learning, develop motivated interfaces, and enhance students' problem-solving competence.

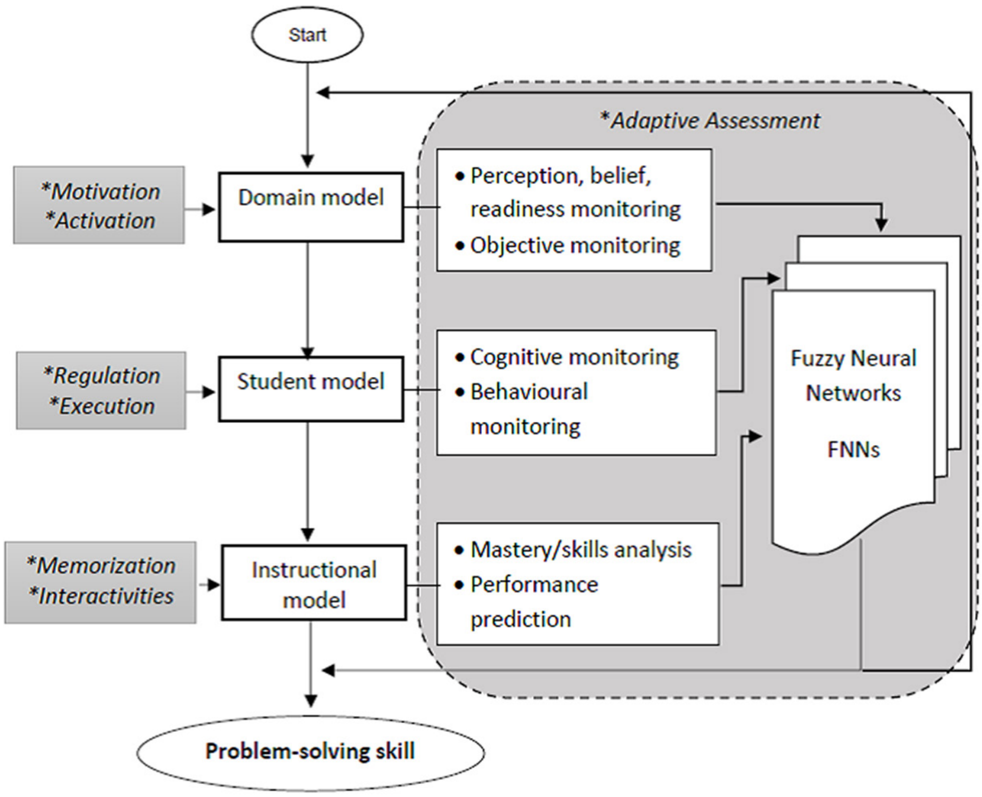

Fig. 5. A conceptual framework of IN-MP-STS

5.1 Motivation

Based on the principle of mechanistic development, an initiator mechanism should include elements that can act as a driving force. Therefore, motivation is a crucial factor that will inspire students in this tutoring system. The combination of inputs in the NNs model, along with motivational elements, will ensure the initiation of learning and can attract students' attention to problem-solving. Motivation arises when there is a clear interest in and understanding of the information. Hence, the fundamental aspect of this tutoring system is to present the elements of problem-solving purposes or goals along with an engaging display. Also, the focus should be on the reward when students are able to complete the task. The management of ideas and emotions should be carefully considered in system development from the outset. In addition, motivation can also be triggered externally through the ITS dashboard or homepage. The combination of design with appropriate colors can attract students as users, eliciting positive emotions. When it comes to internal motivation, the approach to assigning tasks should consider preparedness and the right mindset.

5.2 Activation

This component will ensure that the nerves become active and ready to form a circuit for the process of thinking. This activity will help ensure that students' understanding of NNs in biology is well-developed. This situation is analogous to the strength or orientation of the input available in the system. Therefore, to ensure that this tutoring system can activate the neural circuits, the learning instructions should be delivered using appropriate and creative methods. Instructions do not need to be overly complex in order to ensure that learning coordination does not become stagnant and hinder the enjoyment of learning. As a result, the researcher recommends aligning this element with the input in the system to encourage the student's emotions to reach an optimal level for continued learning, thus maintaining a high level of positive motivation.

5.3 Regulation

Regulation of the learning process occurs when students are able to model their own learning. Tutoring activities that help students achieve the following points indicate a development in learning regulation: staying focused, planning, setting objectives, choosing and determining strategies, acting according to the chosen strategy, consistently monitoring progress, being prepared with alternative strategies, and re-evaluating each process. This situation will enhance planning skills and critical thinking abilities. Therefore, regulatory elements must be present in the tutoring system as a component that can enhance the effectiveness of learning. Regulation is essential because it enables effective learning, ensuring that students are aware of available resources, understand their potential, know how to avoid mistakes, and can focus on their objectives. This component can help students manage their learning while engaging in other activities. In addition, this component should also be a priority in the development of the tutoring system. This is achieved through the ranking of interfaces, activities, and task transfers provided. It requires a systematic arrangement, and each level has an effective detection pattern.

5.4 Execution

Next, the catalyst for this tutoring system needs to be the execution component, which involves coordinating cognitive, behavioral, and metacognitive skills based on the specific needs of actions and operations that are suitable for the learning situation. This medium should include elements that encourage awareness and cognitive engagement, such as problem-solving tasks, challenges or competitions, presentation activities, and more. The phases of the learning activity, especially the climax phase, require students to think and act according to the correct strategy. Enhancing thinking skills can positively impact students' learning efforts and behaviors.

The learning environment should also incorporate real-life experiences, such as those found in the natural environment. For instance, a task that includes authentic images or a video can enhance the likelihood of developing intellectual literacy. Because learning is an experience that applies to all individuals, there is a mindset about the experience, and the process of assimilation becomes easier to occur.

5.5 Memorization

A critical process in learning is also remembering the entire learning material. Therefore, the development of ITS requires memorization components. The learning process should incorporate the principle of effort to ensure optimal brain and mind function, thereby complementing the principle of memory. Among the factors that need to be taken into account are interest, interconnectedness, and existing knowledge. These factors ensure that the brain can coordinate and be prepared to assimilate knowledge. To optimize memorization, the instructional model should include features such as volume control and the design of the content. It needs to be selective and organized. For example, objectives should be aimed at both general and specific goals. In addition, organize the presentation by category or group. In this context, the emphasis should also be placed on the strength and functionality of the neural connection. This can be achieved through individual presentation elements, visualization, and association. Furthermore, assessment components are necessary at every level or stage of the established learning hierarchy.

5.6 Interactivities

Engaging in a task serves as a catalyst for critical thinking, drawing on students' prior experiences and fostering creativity. Activities are transformed into a framework for organizing existing knowledge and experience by modifying them to generate new knowledge or skills. Previous research has demonstrated that multimedia-based learning, carefully structured with supplementary activities, can promote deep learning. Like ITSs, it is a web-based, multimedia learning platform. However, this system will turn students into "grinding machines," only dealing with whatever comes their way and hindering creativity. It arises when problems are solved strictly according to the given instructions and organized requirements. However, if the system is updated with activities such as creating solution infographics, modifying formulas, and conducting forecasting activities. Alternatively, students can explore preliminary results by applying the concept of "if-then" logic, which will help develop their decision-making skills. In addition, activity is a relevant factor in shaping the implementation of knowledge schemes. Critical reflection on action after the completion of simple activities is viewed as a restructuring of a specific scheme or learning concept. This activity should also provide opportunities for all parties involved to equally assess and reflect on their own contributions. Through activities, they not only stimulate the mind, increasing awareness of cognitive structures, but also promote cognitive regulation to enhance understanding of facts, concepts, and computational skills, ultimately improving problem-solving abilities.

5.7 Adaptive assessment

The most critical aspect of ITS is establishing a calibration system that can offer immediate and accurate feedback. The optimal solution would be to develop a calibration system that can function as a "facilitator." It will be a helpful companion for students when using ITS, providing appropriate feedback, and serving as an effective monitor. Therefore, this component should involve multimodal data fusion. FNN is the right choice because it does not have any issues with the orientation of the input data. Furthermore, FNN can be configured with sensors to serve as a recognition system and to receive data inputs. FNNs have flexible properties and can be modified according to data and measurement purposes. The issue with current conventional ITS is that they only offer feedback at the conclusion of the learning process. The assessment does not provide a comprehensive overview of the entire learning process. It lacks an initial assessment at the beginning of the learning process and does not assess the relationship between all the learning processes. Therefore, the ideal system is equipped with learning style and knowledge mastery analysis, learning situation assessment, learner state assessment, and, most importantly, can also accurately predict outcomes as a result of integrating all the previous assessments.

The fundamental principle of learning is to impart new knowledge or skills to students and to assess the effectiveness and suitability of instructional content. The primary focus of this framework's growth remains the delivery and evaluation aspects of each learning session, which are being modified and strengthened. The delivery aspect is enhanced through neuroscience-based mechanistic strategies, while the evaluation aspect is modified by implementing FNNs. The seven elements of motivation, activation, regulation, execution, memorization, interactivity, and adaptive assessment that were introduced will ensure the delivery of mathematics problem-solving skills. Their effectiveness is achieved through the ITS system. The transformation of the delivery system through the neuroscience mechanistic strategy involves six elements: motivation, activation, regulation, execution, memorization, and interactivity. This approach ensures that the true potential of students is taken into account and promotes deep learning. In contrast to the existing conventional strategy, the elements are separated. For example, in the current ITS system, students only follow the available instructions, but they do not take advantage of the students' potential, and their thinking processes are neglected. There is also an ITS module that focuses solely on creating an attractive interface, but it neglects to coordinate students' thinking, thus hindering their ability to customize their learning based on their needs. By prioritizing the six elements mentioned earlier, the interconnectedness between students, their minds, and the system will improve. This goes beyond students simply navigating the system and following all the instructions to complete the task. The assessment aspect is also a key point in learning, not only in ITS applications. Therefore, this aspect necessitates an adaptable and flexible platform. Therefore, it is recommended that FNNs enhance the measurement of certain constructs in ITS, as the system is capable of developing this evaluation component. The adaptive nature of FNNs allows them to be used based on the orientation of the data and the purpose of measurement. The ability to receive input through sensors or data input is very useful for evaluating various aspects, such as the cognitive trajectory and behavioral performance of students. For instance, implementing a sensor on the front camera of the screen enables the ITS system to recognize the gestures and facial expressions of students, thereby assessing their levels of interest, enjoyment, and motivation. Furthermore, the capability of FNNs to process data instantly and solely utilize feed data makes this system safer and less susceptible to vulnerabilities. Then, students will continue to receive immediate and timely feedback, which can be used as support for intervention if necessary.

In practice, enhancements and adjustments to the ITS system make it potentially more widely applicable and less reliant on specific expertise or abilities. Six elements of neuroscience mechanisms and one element of intelligence analysis can be adjusted based on usage and objectives. For instance, if this ITS is used to teach experimental skills or practical work in vocational training, interactive elements in the instructional model within the ITS must be combined with suitable evaluation components. In short, this framework is ready for application and highly adaptable. Several constraints exist, such as the need for specialized research to translate all aspects of the neuroscience-mechanistic strategy. For instance ensuring appropriate levels of activity is necessary to implement these elements. Consequently, a significant amount of time is required to develop the system's content. In this context, there may also be variations in the weighting of elements depending on the skills being presented. Unequal conditions may also arise if it is applied to other subjects. However, the assessment component will continue to be relevant and appropriate through the implementation of fuzzy neural networks.

6 CONCLUSION

To provide guidance for designing and developing ITS or e-learning systems for competence development, this paper initially explores the evolution of learning theory in conjunction with advancements in computer technology and AI. This paper discusses the concepts and design models of ML, ITS, and other technologies, including NNs and their modifications. Here, the development of the methodology required to design a learning system that is adaptive for individuals is discussed. Second, drawing on common elements from previous frameworks, this conceptual framework has been developed to establish a more comprehensive learning system by emphasizing seven key elements: motivation, activation, regulation, execution, memorization, interactivity, and adaptive assessment. These seven elements are important as catalysts for other expertise related to learning and student interaction, aiming to make the ITS learning system more intelligent, ideal, and responsive to students. Finally, this conceptual framework can serve as a guide for designing intelligent adaptive learning systems. Advances in technology, sensors, and data analytics now enable the new generation to develop more capable intelligent learning systems. The neuroscience approach, with the conceptual framework outlined above, is beginning to demonstrate the utility and effectiveness of intelligent learning systems in various fields of use, particularly for critical subjects and complex skills. With a comprehensive understanding of system design and development, it is highly effective and applicable in today's digital learning environment. In addition to being able to adapt the way we learn and train to meet the diverse educational and training needs of society.

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